Reliability analysis and performance optimization of wireless networks and its applications

Dong, Qiumin

2014

Dong, Q. (2014). Reliability analysis and performance optimization of wireless networks and its applications. Doctoral thesis, Nanyang Technological University, Singapore.

<https://hdl.handle.net/10356/60750>

<https://doi.org/10.32657/10356/60750>

Reliability Analysis and Performance Optimization of Wireless Networks and Its Applications

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A thesis submitted to Nanyang Technological University
in partial fulfillment of the requirement for the degree of
Doctor of Philosophy

2014

Acknowledgments

First and foremost, I would like to express the deepest gratitude to my supervisor, Prof. Dusit Niyato. In my four years doctoral program, when I came across big difficulties in the research, Prof. Dusit Niyato always taught me to analyze these difficulties from a different perspective. When I felt frustrated and lost my confidence, he gave me a lot of inspiration. Besides, he sets me a good example on how to be a qualified researcher. He taught me the method of searching useful information among huge data, the experience of mastering mathematical tools, and the good habit of managing time more efficiently. Moreover, he pointed out on the novel research direction which leads me to my research road and gave me a lot of enlightenment on specific details in my research works.

Secondly, I would like to express my deep gratitude to my co-supervisor, Prof. Ping Wang for her invaluable guidance and suggestions on my research project as well as on my attitude about communicating with people and facing difficulties in the life. She and her family also treated me and my group members dinners when we were homesick on Chinese traditional festivals.

Thirdly, I express my sincere thanks to Prof. Zhu Han. He shared a lot of interesting ideas with me and also gave me invaluable instructions on my research.

Besides, I would like to thank our research group members and lab colleagues. We spent happy four years together. The technicians in my lab are all very friendly too. Special thanks for their self-giving help and warmhearted assistance on research facilities.

As a Ph.D. student, I am also very grateful to my university and school for the opportunity they gave to me so that I can come to Singapore, open my eyes to the wonderful research field, and have the chance to be connected with the world.

Finally, I wish to express my deepest gratitude to my parents for their everlasting love, encouragement and support in my life.

Abstract

Nowadays, as unlicensed spectrum becomes a scarce resource, the concept of cognitive radio is proposed as a feasible solution. In a cognitive radio network, the channels that belong to licensees, also named as primary users, can only be accessed by secondary users (i.e., unlicensed users) opportunistically when they are not occupied by primary users. As cognitive radio is utilized to exploit the potential capacity of spectrum, the analysis of reliability and quality of service regarding the packet transmission of secondary users arises as a critical issue.

However, due to estimation error, noise or system state fluctuation, parameters such as channel state (i.e., occupied or idle), channel quality and so on may be uncertain to secondary users. As the first issue studied in our research, the quality of service measures of a cognitive radio network are evaluated with the assumption of uncertain parameters so that the measures in the worst-case and best-case can be obtained and used to analyze the reliability of the cognitive radio network. Dynamic spectrum access of secondary users is arranged according to medium access control protocols. A two-dimensional Markov chain is applied to model the packet transmission of secondary users. A robust optimization method that can solve the Markov chain with uncertainty is utilized to obtain the lower and upper bounds of performance measures.

On the other hand, as information and communication technologies are implemented in smart grid and other systems. Cognitive radio networks and other wireless networks are profoundly penetrated into such systems. The impact of unreliable or imperfect wireless networks on the performance of power usage behavior in smart grid has merit of evaluation. Therefore, the second issue in our research is the deferrable load scheduling under imperfect data communication. Given that the real-time pricing is implemented to realize the demand response in smart grid, a deferrable load can be scheduled optimally so that the power consumption cost will be minimized. However, if the price information is not available occasionally due to imperfect data communication or cyber attacks, the scheduling performance will be compromised. To overcome this problem, a partially observable Markov decision process based deferrable load scheduling algorithm together with the implementa-

tion of a standby alternative channel is proposed to improve the reliability of the data communication in smart grid. The numerical results show that the scheduling performance is improved in the case when the scheduler lacks of actual price information.

Moreover, the impact of imperfect data communication on plug-in hybrid electric vehicle charging scheduling performance of a charging station is quantitatively analyzed in the last part of our research. The scheduling objectives are to minimize the power consumption cost incurred by charging batteries and to allow as many as possible plug-in hybrid electric vehicles to be served. A battery replacement strategy is adopted to save drivers' time. The numerical results show that if there are backup channels that can also be used to receive price information, the degraded scheduling performance due to imperfect data communication can be improved. On the other hand, a multi-stage stochastic programming model is formulated to solve the power supply cost optimization problem for the grid operator. Renewable source generation as well as utilization of energy storage device are integrated into the supply optimization problem.

In summary, this dissertation investigates the upper bounds and lower bounds of quality of service measures for the dynamic spectrum access of secondary users in a cognitive radio network. The impact of imperfect data communication channel on the performance of deferrable load scheduling and plug-in hybrid electric vehicle charging scheduling is analyzed. Some methods for mitigating such negative impacts are proposed.

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Chapter 1

Introduction

This introduction will present overviews of cognitive radio networks and smart grid, the research objectives and motivations of our research, the background of three major issues studied in this dissertation and the problems that need to be solved in later chapters.

1.1 Overview of Cognitive Radio Networks

1.1.1 Spectrum Access Models

Traditionally, the radio resource (i.e., spectrum) is assigned to the licensed users and cannot be shared by other users. However this static licensing scheme which is also called “command-and-control” scheme will result in spectrum under-utilization [1–4]. The limitation of this “command-and-control” scheme can be summarized in several aspects. In the first place, once the spectrum is assigned to a licensed user, the license of the spectrum cannot be granted to a new service provider even when the spectrum is under-utilized by the original licensee. In the second place, as time goes on, the customers’ interests will change, which leads to the case that some services on some spectrum become less popular and finally stop (e.g., analog television [TV] service). Then the spectrum which is not being used will become available for other services. In the third place, the traffic load for certain service on a licensed spectrum may not be uniform in a large scope of region. Then the spectrum might be under-utilized at some small areas in the region. To overcome the limitation and fully exploit the utilization of spectrum, the technique of software-defined radio [5, 6] is im-

plemented. The transmission parameters such as operating frequency band, modulation code, and control protocols can be adjusted dynamically according to the real-time wireless communication conditions in a software-defined radio. Networks that adopt the technique of software-defined radio are named as cognitive radio networks. In the research field of cognitive radio networks, several flexible spectrum access models are proposed and can be classified into three categories: exclusive-use, share-used, and commons.

In the exclusive-use model [7], the licensee of certain spectrum can grant the right of accessing the spectrum to a cognitive radio user who acts as an unlicensed user, but can exclusively use the spectrum once it makes a contract with the licensee and it will not be interrupted by the licensee during the period of time specified in the contract. The lease contract can be valid for a long period of time even for a few weeks and the spectrum access model defined by the lease contract is known as long-term exclusive-use model. In this model, even the type of wireless service can be changed by the cognitive radio user as long as that is permitted by the lease contract. The lease contract can also be valid just for a short period time. Hence, at different points in a relatively long period of time, the cognitive radio users permitted to use the spectrum can be different.

In the share-used model, a secondary user (i.e., an unlicensed user) can opportunistically access the channel even without being granted the permission by the primary user (i.e., the licensee) as long as the transmission of the primary user will not be affected by the secondary user. According to the access style, the share-used models can be further divided into two categories: spectrum overlay and spectrum underlay. In the case of spectrum overlay [8], the secondary user can only access the spectrum when it is not occupied by the primary user. However, in the case of spectrum underlay [9], the spectrum can be accessed by the secondary user and the primary user simultaneously as long as the transmit power of the secondary user is below a certain threshold so that the transmission of the secondary user is as a bit of tolerable noise to the primary user.

The spectrum commons model [10] is designed for the spectrum that is not owned by a primary user. In this model, all secondary users have equal rights to access the spectrum. If the spectrum access is not controlled by a group of secondary users or by any other controllers, this kind of spectrum commons model is recognized as the uncontrolled-commons sub-model. Since there is no control in uncontrolled-commons sub-model, interference will apparently happen. To avoid the interference and to minimize collisions among secondary users, the managed-commons sub-model [11] is proposed. In managed-commons sub-model, a set of autonomous rules are formed and should be obeyed by all secondary users. The spectrum access is controlled jointly by a group of secondary

users in a distributive manner. The last type of spectrum commons model is private-commons sub-model. In a private-commons sub-model, the secondary user must obtain the approval from the primary user before accessing the spectrum. The approval will also specify the transmission parameters such as time, frequency band, and transmit power for the secondary user.

Applying one of the three spectrum access models, available spectrum that is temporal variant or spatial variant can be utilized by secondary users dynamically. In other words, the dynamic spectrum access (DSA) [12] in a cognitive radio network can be realized.

1.1.2 Dynamic Spectrum Access Architecture

The architecture of cognitive radio network can be either infrastructure-based in which the transmissions of the secondary users are handled by a base station, or infrastructureless in which there is no base station and the transmissions of the secondary users are handled by themselves [13]. The transmissions can be either single-hop or multi-hop. For single-hop, if the architecture is infrastructure-based, then the transmissions between all secondary transmitters and secondary receivers are relayed by a unique base station. If the architecture is single-hop and infrastructureless, the transmission between each pair of secondary transmitter and receiver is in a peer-to-peer style. For multi-hop, multiple base stations will act as relay stations for each pair of secondary transmitter and receiver in the infrastructure-based architecture, or several neighboring secondary users will play the role of relay stations for the transmission between their neighboring pairs of secondary transmitters and receivers in the infrastructureless architecture. Moreover, the type of architecture can be also divided into either centralized or distributed. For the type of centralized, the architecture should also be infrastructure-based. Besides, a unique base station will act as the central controller for the secondary system in terms of collecting spectrum information, making decisions about spectrum access, and broadcasting instructions to the secondary users. In contrast, for the class of distributed, the architecture can be either infrastructure-based or infrastructureless. The secondary users collect the spectrum information and make decisions on spectrum access by themselves. Though it may make the design of the secondary transmitters become more complicated, it will incur less communication overheads than that of the centralized architecture.

1.1.3 Spectrum Sensing

There are three ways for the secondary users to obtain information about the availability of spectrum. The first one is database registry which means that the information about the availability of spectrum is stored in a central database that can be updated by the primary users and can be accessed by the secondary users. The second one is called beacon signals which means that the primary users will pass the information about the availability of spectrum to the secondary users through beacon signals. However, because the transition of spectrum state usually happens abruptly, when the secondary user obtain the information about the spectrum state, the spectrum state may already change to another phase. Hence, the last one, spectrum sensing [14] becomes the most appropriate way for the secondary users to know the present state of the spectrum. Other than the previous two methods, spectrum sensing will not incur any modification or extension to the current infrastructure of the licensed network.

Spectrum sensing is performed by the secondary user periodically. Once the spectrum is sensed to be idle, the secondary user will access the spectrum during the rest time of the period. Then at the beginning of the next period, the spectrum sensing will be performed again. However, if the primary user resumes to use the spectrum again before the next period starts, then the interference to the primary user will happen. In order to reduce the impact of the interference on the transmission of the primary user as well as to ensure the performance of the secondary user's transmission, the length of the period should be well designed.

Spectrum sensing can be cooperatively centralized [15] in which a central controller collects the sensing results from all secondary users, processes them and sends instructions about spectrum access to all secondary users after making decisions. Spectrum sensing can also be cooperatively distributed [16] in which there is no central controller and the sensing results are communicated and shared among the secondary users themselves. In cooperative distributed spectrum sensing, each secondary user makes its own decision about spectrum access based on the information either obtained through its own spectrum sensing or from other secondary users. To improve the accuracy of spectrum sensing as well as to reduce the transmission overhead incurred by sensing, wireless sensor network is proposed to be used for spectrum sensing. Wireless sensors are deployed at several spots in an area where the secondary users want to perform dynamic spectrum access. The sensors will sense the spectrum and send the sensing results to their corresponding secondary users, then the secondary users will make decisions about spectrum access by themselves.

Medium access control (MAC) protocols are responsible for spectrum sensing, for instance, decides which channel to sense. After obtaining accessible channels, MAC protocols are used to synchronize secondary users' transmitters and receivers, and schedule the channel access of multiple secondary users to avoid conflicts. More details of MAC will be given in subsection 1.4.1.

1.2 Overview of Smart Grid

Next, as the deferrable load scheduling and plug-in hybrid electric vehicle (PHEV) charging problems in smart grid are studied in our research, an overview of smart grid is given as follows.

1.2.1 The Concept of Smart Grid

In the traditional power grid, interactions between consumers and power grid are quite limited. Power price is usually announced manually through radio broadcast, TV, newspapers or other public media to consumers. As power price is normally fixed for a long period of time (e.g., several months), consumers cannot save cost through shaping their power consumption behaviors. The statuses of transmission lines, distribution substations as well as consumers' power consumption record are monitored by analog devices. Meter data is collected manually by personnel of grid or public utility. As a result, there is a latency between the change of status and the awareness of grid operator, which causes regulation difficulties to the grid operator. Moreover, in traditional power grid, if some accidents or problems happen on the transmission line or any power distribution substations, the part of power grid that is affected by the accident cannot be notified and healed by itself since there is no sensor placed on the transmission line or power distribution substations to detect the problem, and there are no automated controls to respond the problem or to switch to backup transmission line or devices. In all, in traditional power grid, each part (e.g., power plants, transmission line, power distribution substations, customers and so on) cannot share the information possessed by each other. Hence, the scheduling that can balance the profit of each side cannot be achieved and the infrastructure of the power grid is vulnerable to the problems and attacks. To enhance the connection between different parts of the traditional power grid and enable comprehensive scheduling as well as achieving the ability of self-healing, many techniques such as data sensing, control devices, and data communication are integrated with the traditional power grid to promote it to the next generation which is called smart grid [17].

In smart grid, smart meters are deployed at electricity production, transmission, distribution and consumption parts of the power grid to monitor the statuses of these parts, record measurement data and transmit meter data to the central controller or share the information with each other through two-way communication networks. The essential functions of smart grid include self-healing, attack resistance, high quality power assurance, consumer participation, accommodating generation options, enabling electricity market, optimizing assets, and enabling high penetration of intermittent generation sources. Self-healing means that the smart grid can recover from malfunction or at least mitigate the influence of the accident all by itself based on the meter data obtained from embedded sensors and decisions made by automated controllers [18, 19]. By possessing the ability of self-healing, smart grid can become more resistant to attack and can assure high quality power provision. Consumer participation overcomes the shortage of traditional power grid mentioned previously by permitting the consumers to change their power consumption behavior dynamically according to the instant changes of power price. Accommodation generation options means that in smart grid the consumers are allowed to self-generate renewable power through small-scale solar photovoltaic energy system or tinny wind turbine generators [20] and sell excess power to the grid. In another word, the concept of electricity market is re-defined, because sometimes the consumers can play the role of sellers of electricity and the smart grid system plays the role of buyer. With the help of smart meters and automated controllers, the operations can be minimized and the maintenance costs can be reduced in smart grid as compared with the traditional power grid. In this way, the capital assets of the original power grid can be optimized in smart grid. Since the renewable energy is usually generated from resources such as sunlight and wind which are very easily to be affected by climate, weather and other environmental factors, the renewable power generation process will probably be intermittent. Smart grid allows these intermittent generation sources to be integrated into the entire system.

1.2.2 The Structure of Wireless Networks for Smart Grid

Networks and data transmission techniques used to build the two-way communication are very important for the smart grid to support the aforementioned functions, and also constitute the area where our research interests focus on. In the following, we give a brief introduction to the structure of wireless networks [21] in smart grid and the techniques that can be used in each network.

The wireless network architecture [22] in the smart grid consists of three parts: home area network (HAN), neighborhood area network (NAN), and wide area network (WAN), which are shown in

Fig. 1.1.

Figure 1.1: The architecture of wireless networks in smart grid.

HAN is used to connect the sensors, the actuators which are installed inside the home appliances in a house and the smart meter placed in the same house. The data regarding the amount of power consumption is collected by the sensors and transferred to the smart meter through HAN [23]. The real-time meter data will be then transferred through other sub networks in the network architecture and finally to the meter data management system (MDMS) for dynamic pricing and deterministic direct load control. Then the instructions for load control or other issues are sent back to the smart meter and through the relay of the smart meter to the actuators. The actuators read these instructions and convert them into actions by setting the values of different parameters of the home appliances. If the instruction is about load control, either the action of increasing or decreasing the amount of power consumption will be taken. Since HAN only covers a short-range of area, techniques such as WiFi or ZigBee can be used to build up the HAN.

In a residential community, multiple HANs in multiple houses are connected by NAN. As mentioned previously, the meter data collected by the smart meters are then transferred by HAN gateways to data aggregator unit (DAU) through NAN. Sometimes, the smart meters can act as HAN gateways directly. Network technologies such as WiFi or cognitive radio network [24,25] can be used to build up NAN.

WAN is used to connect NANs, sensors and actuators implanted in other parts of the smart grid such as power generators in the power plants, transmission lines, and power distribution substations. The meter data buffered at a DAU can be retransmitted to the MDMS through WAN. DAU can serve as the NAN gateway and technologies such as cellular network or broadband wireless access can be used for the data transmission between the gateway of NAN and the MDMS, while the gateways of WAN apply 3G, satellite, or WiMAX [26] to collect meter data from the sensors placed in each part of the smart grid.

1.2.3 The Importance of Reliability Analysis of Wireless Networks to Smart Grid

The wireless networks will be intensively integrated into many subsystems (i.e., power delivery system, power distribution system, residential houses, industrial premises and so on) of smart grid. On one hand, the penetration of wireless networks improves the regulation efficiency of grid systems and provides other aforementioned benefits. On the other hand, as the interconnection between the wireless networks and grid systems becomes more and more coherent, the unreliability of wireless networks will incur negative influence to the grid that cannot be neglected. The reliability of wireless networks in smart grid can be effected by several factors. For instance, one factor could be the interference due to the coexistence of heterogenous radio systems implemented in HAN, NAN and WAN. Besides, malfunctions of either hardware or software in smart meters, DAUs, routers, and other equipments will also result in disconnections that could affect the reliability of networks. Moreover, the reliability could be endangered by malicious cyber attackers. Attackers may manipulate or falsify power price information to disturb the power market with the objective to gain monetary profits [27]. The other objectives could be originated from terrorism or military purposes. Note that, in traditional power grid, it is hard to deteriorate the integrity and availability of price information. However, in smart grid, as the price information is transmitted through communication networks, it becomes vulnerable to cyber attacks.

When disconnections happen, the information pertaining to customers' power demand collected by smart meters cannot be successfully transmitted to the MDMS. As a result, it could be difficult for the grid operator to regulate power consumption during peak hours or make correct decisions on pricing. Disconnections in WAN will affect the awareness of grid operator on the statuses of transmission lines and substations in the distribution system. For the aspect of downlink, the load control orders issued by the MDMS cannot be transmitted to smart meters and executed by actuators. As a result, the performance of load management or self-healing will be degraded. For the cyber

attacks, the confidentiality, the integrity, and the availability of information communicated among components in smart grid will be harmed, which threatens the security of the grid systems and incurs additional costs.

The reliability of wireless networks is recommended in several works to be improved through modifying the default routing protocol [28], enabling DAUs to perform cooperative communication to transmit meter data to MDMS [29], sensing and managing interference [30], or scheduling data traffic [31]. The methods originally used to analyze the reliability of wireless networks alone such as universal mobile communications system [32], wireless local area networks [33] and wireless sensor networks [34] can also be revised and adopted to evaluate their counterparts in smart grid. Some other papers focus on studying the reliability of wide-area measurement system that is a subsystem of smart grid used to monitor power delivery status [35, 36]. For the aspect of security, the disturbance to power market caused by jamming price signals has been analyzed [37]. Some intrusion detection systems have been proposed [38, 39]. However, few works in the literature analyze the impact of reliability of wireless networks on power consumption in smart grid, which constitutes the main merit of the issues studied in this dissertation.

1.3 Research Objective and Motivations

1.3.1 Research Objective

In this research, we aim to analyze the reliability of wireless networks, especially the cognitive radio network, through investigating the quality of service (QoS) measures of the network in the worst and best situations with the assumption that some parameters can be uncertain. Furthermore, as the prevailing of information communication technologies and integration of wireless networks into systems such as smart grid, we aim to evaluate the impact of unreliable wireless networks on the benefits of participants such as customers or system operators in these systems. The objective is achieved in three steps. First, the lower bounds and upper bounds of QoS measures regarding the packet transmission of secondary users are obtained given uncertain parameters. Second, the deterioration to the benefits of power consumers in smart grid when the agent of customer (e.g., power consumption scheduler) cannot receive vital information such as power price occasionally due to imperfect wireless networks is assessed. Third, we focus on PHEV charging stations and study how the benefits of stations owners will be impaired if the charging cannot be scheduled

optimally due to intermittent data communication. Moreover, in the second and third steps, we also try to provide some feasible methods to alleviate the negative impact caused by imperfect data communications.

1.3.2 Motivation

For the first issue in our research, we are motivated by the fact that in practical wireless environment, channel state, channel quality, and other parameters can be unstable and fluctuated. In addition, due to estimation error and noise, secondary users cannot precisely obtain these parameters. However such uncertainty usually is not taken into account by most of existing works that study the DSA problem. The negligence about the uncertainty of parameters may be acceptable in ideal cases, but in practical cases if parameters take values different from the definitive nominal values, the results of the analysis can be dramatically inaccurate. Hence our research is motivated by the purpose of analyzing the MAC for DSA under uncertainty and discussing the impact of uncertainty on the QoS performance of the secondary system.

As the next generation of power grid system, smart grid integrates information communication technologies (ICT) [40] to build two-way data transmission routes so that the information can be communicated in real time between the customer end and the grid operator end. On one hand, the integration of ICT can improve the regulation of grid system and reduce operation cost. On the other hand, communication networks, especially wireless networks may suffer from interference, congestion, malfunction in devices or even cyber attacks. Therefore, it is important for the system designers to be aware of unreliable wireless networks' influence on the system performance and whether there are some feasible solutions to mitigate such impact. Motivated by this purpose, the second part of our research is directed to the deferrable load scheduling in smart grid with imperfect data communication channel.

The third part of our research is motivated by the same reason. But we focus on studying the impact of unreliable channels on PHEV charging scheduling performance of charging stations. As the relatively long charging time is one of the obstacles that hinder the popularity of PHEV. In our research, we assume that a charging station can adopt the battery replacement strategy to save the time of PHEV drivers. Besides, as the penetration of PHEVs into smart grid, the power demand due to PHEV charging will increase. It is prudent for the grid operator to arrange the power supply optimally. Therefore, the power supply optimization is also considered as an important issue in our

study.

1.4 Research Focus

The three issues studied in this dissertation are summarized as follows.

1.4.1 Medium Access Control for Dynamic Spectrum Access in Cognitive Radio Networks: Analysis under Uncertainty

As aforementioned, MAC protocols in a cognitive radio network are responsible for spectrum sensing and spectrum access. In the aspect of spectrum sensing, MAC protocols make optimal decisions on the selection of spectrum to be sensed. In the aspect of spectrum access, the functions of MAC protocols are two-folded. On one hand, MAC protocols prevent secondary users from interfering the transmission of primary users through forcing them vacate channels when primary users return (i.e., overlay mode) or through confining the strength of secondary users' signal so as not to exceed the tolerance threshold of primary users (i.e., underlay mode). On the other hand, MAC protocols take charge of channel access coordination among secondary users [41] to alleviate collisions so that available spectrum resource can be efficiently utilized.

The MAC protocols considered in our research is implemented by a centralized controller (e.g., access point/base station). We focus on a share-used overlay spectrum access model. Specifically, as aforementioned, in such model, primary users will not grant permission to secondary users for exclusive usage of their licensed channels. Different from the underlay model, secondary users opportunistically access vacant licensed channels when primary users are in idle state. The centralized controller that implements MAC protocols is responsible for spectrum sensing. It manages several interfaces and controls them to cooperatively sense several licensed channels. After sensing results are obtained, the controller is also responsible for the decisions of spectrum access. Because available spectrum resource is limited, without coordination or negotiation among secondary users, collisions will happen when more than one secondary users have packets to transmit [42]. In our research, it is assumed that a round-robin rule [43] is adopted by the controller so that the chance of spectrum access can be equally allocated to all secondary users.

The transmission of secondary users, the state variation of licensed channels, and the coordination

actions of the controller in the secondary system are formulated coherently as a queueing model. Metrics such as packet dropping probability, queue throughput, and average delay are used as QoS measures to evaluate the performance of dynamic spectrum access when the MAC protocols are applied by the centralized controller. Because the accessing habits of primary users may vary from time to time, which causes the state transition probabilities of licensed channels hard to be measured precisely. Besides, there may exist estimation error and noise. Therefore, different from related works on this issue, the channel state transition probabilities are assumed to be uncertain in our research. A method that can manipulate Markov chain with uncertainty is utilized to obtain the stationary probabilities of the queueing model under uncertainty. The upper bounds and lower bounds of QoS measures are obtained and compared with nominal values. Further details are provided in Chapter 3.

1.4.2 Deferrable Load Scheduling under Imperfect Data Communication Channel

In power grid system, generation units, transmission and distribution systems are designed and deployed to enable the grid being capable to endure the maximum power demand during peak-hours. As the growth of population of human being as well as world economy, the power demand increases year by year [44]. One way to handle the increasing power demand is to expend generation units and enlarge the capacity of transmission lines and the distribution system. However, this method requires a lot of investments and still cannot reduce the peak-to-average ratio in power demand which makes the grid inefficient, because during off-peak hours, the expanded capacity of generation units will be under-utilized.

With the aid of ICT, in smart grid, the increasing power demand can now be tackled from the side of consumers through the demand-side management (DSM). As the name implies, DSM aims to manage the load on consumers' side so as to reduce consumption in peak hours or to shift consumption from peak hours to off-peak hours. With DSM, the potential of existing grid facility can be exploited. As a result, the investment on generation and transmission expansion can be saved as much as possible. Moreover, with the exploitation of renewable sources, DSM can be used to shape the demand curve to be adaptive to the volatile renewable source generation [45, 46].

Demand response (DR) is a predominant implementation form of DSM [47]. There are two kinds of DR programs. One kind of DR program uses rebate or credit as an incentive to encourage consumers to change their consumption behavior. Or the grid operator can even directly control the

appliances of consumers based on contracts made with consumers [48–50]. However, our research focuses on another kind of DR program, the real-time pricing (RTP) [51, 52]. In a traditional power grid, power price is announced manually to consumers and usually is fixed for a relatively long period of time. While, in smart grid, as the bidirectional communication route is established between the grid operator and consumers. Based on the power demand and supply information gathered from consumers' side and generators' side respectively, the operator can make decisions on pricing in a real-time style and disseminate the price information to consumers through the hierarchical network infrastructure. The real-time price will be displayed by smart meters installed in consumers' premise. In order to curtail power demand during peak hours and flatten the demand curve, power price will usually be set high in peak hours to eliminate unnecessary power consumption. In return, the reduced consumption can be resumed in off-peak hours at lower power price which is provided as an incentive to stimulate the shifting. The time and price elastic power consumption units (e.g., washer, dryer, refrigerator, dishwasher, air conditioner) that do not require immediate execution is named as deferrable load. The scheduling of deferrable load with the objective to make consumption be adaptive to RTP and reduce consumption cost of consumers constitutes the second issue in our research. Instead of manually adjusting consumption of home appliances by consumers themselves, an energy consumption scheduler is embedded into a smart meter [53] to realize autonomous load management. Based on the price information sent from grid operator and the requirement from consumers such as deadline to finish the load, the scheduler makes decisions on power consumption behavior optimally. Load regulation instructions will be sent by the smart meter to home appliances through HAN in each decision epoch.

In our research, a deferrable load scheduling algorithm that can be applied by the scheduler is proposed with the objective to minimize power consumption cost and to reduce deferment times. However, when the data communication in smart grid suffers from interference, congestion, malfunction in devices or even cyber attack, it is possible that the power price information cannot be transmitted successfully to the scheduler. As a result, the scheduling performance will be negatively affected by the suboptimal decision making due to incomplete power price information. To quantitatively evaluate the impact of imperfect data communication channel on the performance of deferrable load scheduling, the scheduling problem is formulated as a Markov decision process (MDP) for the case with complete price information and the case with incomplete price information. Moreover, a partially observable Markov decision process (POMDP) based scheduling algorithm is proposed to mitigate such negative impact. The benefit of applying a standby channel is also investigated. The details will be elaborated in Chapter 4.

1.4.3 An Adaptive Scheduling of PHEV Charging: Analysis under Imperfect Data Communication

Environment crisis such as air pollution and global warming receive more and more public concerns. In order to reduce green house gas emission and the dependence on fossil fuel, electric vehicle (EV) is proposed as an alternative for the conventional vehicles. As oil price goes higher and higher, compared with conventional fossil fuel-based vehicles, EVs have lower operational cost. However, the driving range of EVs is shorter than that of conventional vehicles. Before the prominent revolution of battery technologies, PHEV can be a good choice before complete shifting from conventional vehicles to EVs happens.

Plug-in refers to a plug that is usually in the rear of a PHEV and can be fitted in a standard socket located in a house or a charging station to let the PHEV get charged. Hybrid means that PHEV can run in two modes [54]. One is the charge-depleting (CD) mode. In CD mode, batteries provide power for the vehicles. As a result, the energy in batteries is depleting during this mode. The other is the charge-sustaining (CS) mode. In CS mode, fossil fuel takes the place of batteries and provides power for the vehicles. Because a PHEV does not only rely on the electricity energy and a gas station is more easier to find. Compared with EVs, the problem of range limitation is relieved for PHEVs.

Three charger power levels can be chosen for PHEV charging according to charging requirements on charging time, location, cost, and equipment [55, 133]. Level 1 charging is suitable for charging overnight at residence as it usually will take more than 10 hours. Though level 1 charging is the slowest one, the cost of charger infrastructure is the lowest. Level 2 charging consumes less than 10 hours and is suitable for temporarily parking in parking lots located in shopping mall, campus or other public facilities. Both level 1 and level 2 charging use alternating current (AC) and is called on-board charging. Because a charger installed inside a PHEV is responsible for charging directly. The on-board charger has a AC to direct current (DC) convert to convert current and charge the battery. While level 3 charging needs a off-board separate charger. The level 3 charging is also called DC fast charging. In level 3, charging can be finished in less than an hour. But the infrastructure cost in the highest in the three levels. Hence, level 3 charging is more suitable for charging stations owned by companies.

In our research ,we focus on studying the level 3 charging, specially for charging that happens at charging stations. As RTP is implemented in smart grid, similar to the second part of our research,

we aim to propose a PHEV charging scheduling algorithm that can be adaptive to dynamic price and incurs the minimum power consumption cost. However, scheduling can hardly be performed in conventional charging stations. Because PHEVs have to park beside chargers during the charging process, drivers need to wait till the charging is finished. Therefore, even when the current power price is high, drivers will be reluctant to accept requests that their PHEVs are scheduled to be charged later. To solve such problem, a battery replacement strategy is adopted by charging stations studied in our work. When a PHEV arrives at a charging station, a staff will dismount the depleted battery off the PHEV and replace it with a fully charged battery. The replacement procedure can be finished in a few minutes. The charging scheduling can be performed on dismounted batteries in an off-line mode. As a result, not only drivers' time can be saved, but also the scheduling can be enabled. As real-time price information is transmitted from the management centre of grid system to the smart meter in a charging station, when data communication channel fails, the scheduler of the charging station cannot receive the price information. Consequently, the scheduling performance will be affected. In our research, the scheduling problem is also formulated as a MDP model and the impact of imperfect data communication on the scheduling performance is analyzed. Besides, the effect of multiple channel access on mitigating such impact is discussed. The proposed scheduling algorithm is also designed with the objective to reduce the number of rejected PHEVs and to be flexible to different performance requirements. Moreover, as PHEV charging will consume a lot of power [56]. The power demand distribution of several charging stations in each stage (i.e., a time period) is derived. A power supply optimization scheme is proposed to minimize the supply cost for the sake of grid operator. More details can be find in Chapter 5.

1.4.4 Connections among Research Issues

With the aid of ICT, smart grid becomes a promising selection for the next generation of power grid. Because of ease implementation and other advantages, wireless networks will be widely used in smart grid. Particularly, as the cognitive radio network can exploit the potential of licensed spectrum, provide a remedy for spectrum scarcity, and incur less cost (e.g., operating cost, cost for purchasing licensed spectrum and so on) [25, 57] to utilities compared with other wireless communication techniques, it can be adopted for data transmission in some parts (i.e., neighborhood area network) of smart grid. The reliability of wireless networks including cognitive radio networks is vital to the performance of smart grid [58]. Therefore, for the first issue (i.e., Chapter 3), we evaluate the QoS measures of dynamic spectrum access in a cognitive radio network in the worst-case

and the best-case. After that, for the second issue (i.e., Chapter 4), the impact of the reliability of wireless networks, especially the cognitive radio networks on the performance of deferrable load scheduling in smart grid is discussed. PHEV can be considered as a special case of deferrable load. However, most of existing papers focus on studying the PHEV charging scheduling in residential houses or parking lots where Level 1 or Level 2 chargers is usually used, and the parking duration is longer than charging duration (i.e., the cumulative time length for battery being charged). But in the third issue (i.e., Chapter 5), the charging scheduling in charging stations that apply charger power Level 3 is studied. The impact of imperfect data communication is again analyzed for the PHEV charging scheduling performance.

1.5 Organization of the Chapters

The rest of this dissertation is organized as follows:

Chapter 2 Related works in the literature on the three issues studied in our research are briefly reviewed in this chapter.

Chapter 3 The performance of MAC is evaluated with the assumption that channel state transition probabilities are uncertain. The upper bounds and lower bounds of performance measures are obtained and analyzed.

Chapter 4 The problem of deferrable load scheduling in smart grid is formulated and solved. The impact of intermittent price information due to imperfect communication on the scheduling performance is analyzed.

Chapter 5 The problem of PHEV charging scheduling is formulated and solved for charging stations that adopt the battery replacement strategy. The impact of incomplete price information on the PHEV charging scheduling performance is evaluated. The power supply optimization problem is solved for sake of the grid operator.

Chapter 6 The contributions of this dissertation are summarized. Possible directions of further work are outlined.

Chapter 2

Literature Review

2.1 Related Works on Medium Access Control for Dynamic Spectrum Access

In cognitive radio network, channels are allocated to primary users. For a secondary user to access the channel, the target channel must be sensed to be idle. However, sensing the channel incurs overhead and can degrade the performance of transmission. An optimization for channel sensing to maximize discovered spectrum opportunity and to minimize channel access delay was proposed in [59]. The similar problem was considered in [60], for which an optimal stopping problem was formulated to determine optimal number of channels to be sensed. An optimization for the problem of channel sensing and channel access was formulated as a POMDP model in [61]. Given the two-state channel activity model, an optimal policy in terms of the set of channels to be sensed and the set of channels to be accessed was obtained, with the objective to maximize the number of transmitted bits while the probability of collision to the primary user is maintained at the target level. However, none of these works considered the impact of dynamic spectrum access to the radio-link level queueing performance. In this case, the queueing performance will be affected not only by channel quality, but also by the activity of the channel (e.g., either idle or occupied by a primary user).

The queueing model for cognitive radio network was proposed in [62] considering both physical and MAC parameters. The system model considered a dynamic cognitive radio scenario in which available spectrum opportunities are aggregated and secondary users use this aggregated spectral

bandwidth as a single channel for transmission. Although multiple secondary users were considered, their packets were aggregated into a single queue. In addition, since M/G/1 queueing model was used, the correlation of channel activity and channel quality cannot be captured. In [63], a queueing model based on discrete-time Markov chain (DTMC) was developed for dynamic spectrum access. The correlations of channel fading and channel activity of primary users were captured in this model. However, the system model considered only single secondary user (i.e., no scheduling). Also, channel sensing mechanism was ignored, and hence the sensing policy at medium access control layer was not optimized.

In the literature, there are some works analyzing spectrum sensing and accessing strategy by using continuous-time Markov chain (CTMC) to model the state of channel. In [64–68], the two-state (i.e., idle and busy) CTMC was used to model primary users' occupancy at each channel. In [64–66], holding time and idle time of each channel were assumed to be exponentially distributed. Based on this assumption, in [64] and [65] a primary user's action was not assumed to be slotted, and the primary user can access a channel at any time. In contrast, a secondary user's action was modeled to be time-slotted and an opportunistic accessing strategy was proposed. Based on the two-state CTMC model and utilizing past channel activity histories, a proactive channel access strategy was proposed in [66]. In [67], the sojourn time of each state follows an arbitrary distribution, and an M/G_y/1 queueing model was applied to study the performance of MAC protocol. In [68], it proposed a transmission scheme which aimed to reduce the time-averaged cost.

Instead of considering a channel as two-state CTMC, in [69] each channel can have more than two states and these states represent different cases wherein the channel is idle, occupied by different secondary users, or occupied by primary users. Moreover, it provided a comparison with existing two-state model, and derived the stationary state probabilities. In [70], the CTMC was also used, but the state of each channel has two dimensions. One indicates the number of primary users using this channel at certain time instant, and the other represents the number of secondary users competing for the channel at the same instant. To reduce the interference due to competition among multiple secondary users for the same channel, [70] proposed a two-phase framework consisting of the first phase in which a secondary user estimates the traffic parameters of other secondary users nearby and the second phase in which the secondary user performs opportunistic spectrum access. On the other hand, in [71–76] instead of the CTMC, the DTMC was used to model the usage pattern of each channel. A two-state transition matrix was used to describe the channel fluctuation between idle and busy states. Based on this assumption, in [71], a channel-hopping based cognitive radio MAC scheme was proposed and the mean and distribution of detection time were analyzed in [72].

In [73–75] several optimal channel sensing strategies were proposed. In [76], a secondary user was allowed to switch to the channel with the highest idle probability whenever the current channel's throughput was below a derived threshold. Compared with previous papers that used definitive parameters of channel state, in [77], the author provided an approach to estimate these parameters and used the approximate values in the analysis.

However, none of these papers considered a system scenario where the parameters of channel state in a Markov chain are uncertain. In all queueing models presented in the literature, they assume the exact values of system parameters to be available which may not be true in reality. In practical wireless environment, channel state, channel quality, and other parameters can be uncertain and fluctuated. In addition, due to estimation error and noise, secondary users cannot precisely obtain these parameters. In this situation, if the parameters take values different from the definitive nominal values, the results of the analysis can be dramatically inaccurate. To address this problem, we apply a robust optimization method [78] to develop a queueing model under uncertainty for the cognitive radio network. With this method, we obtain the lower bound and upper bound of QoS measures under uncertainty. In addition, the analysis can be used for the selection of system parameters so that the system can operate reliably even under uncertainty. Therefore, this constitutes the main contribution of Chapter 3.

2.2 Related Works on Reliability Analysis and Deferrable Load Scheduling in Smart Grid

As smart grid becomes a promising candidate for the next generation power system, recently more attentions have been focused on studying the reliability of smart grid. Especially, due to the coherent connection between the data communication networks and the power system in smart grid, a lot of works analyze the reliability of the smart grid data communication networks as well as its impact on the power system. In [79], three-level architecture (i.e., device, network, and service levels) is proposed for assessing reliability of communication network in smart grid. At the device level, the parameters (e.g., failure rate and repair rate) of the communication components are collected. These raw data are processed by a reliability block diagram based path-tracing method at the network level to calculate reliability of the overall network. Then at the service level, the impact of the network failure on the stability and reliability of operational and management services is evaluated. In [80], the drawbacks of commonly used models and methods of reliability analysis are discussed.

Then some novel directions are proposed, which can overcome the difficulties in analyzing the complicated communication system in smart grid. In [81], a simulator program for analyzing the communication network in smart grid is developed. Three communication network topologies are analyzed by the proposed simulator. From the simulation result, it can be observed that some links have higher importance than that of other links. The simulation results also show the benefit of a re-routing algorithm used when the default link fails. In [82], a multigate mesh network architecture that expands the hybrid tree routing of the IEEE 802.11s is proposed. Inside the mesh network, there are multiple gateways implemented to guarantee that the reliability, quality of service requirement can be satisfied. In [83], the availability of communication components (e.g., HAN gateways and NAN gateways) is analyzed through the dependency diagram. Then the costs of power over-supply and power under-supply (as well as the cost of device damages) are analyzed from a perspective of public utility with the assumption of disconnections.

On the aspect of deferrable load scheduling or power consumption control, there is also some work in the literature. In [84], the power consumption control of the deferrable load, specifically the electric water heating and storage system, is discussed. The purpose of the power consumption control is to balance the demand and supply in the power system so that the fluctuation of power frequency can be reduced. In [85], binary particle swarm optimization (BPSO) is used to solve the scheduling problem of interruptible load. In [85], the interruptible load can belong to industrial consumers who own spare power generator or can easily reschedule the power consumption plan. The BPSO based algorithm is shown to be able to achieve the total curtailment and payment requirement. Besides, the algorithm does not violate the tolerance limit of the interruptible load and the frequency of interruption can be constrained. In [86], the power consumption scheduling of the deferrable load with price uncertainty is studied. The statistical information about price is used for estimating the future price. The objective is to find an appropriate threshold to start the deferrable task so that the expected cost can be minimized. The results show that even mismatched modeling and parameters' estimation error exist, the load scheduling can still save the consumers significantly. In [87], three heuristic causal scheduling policies for the deferrable load are proposed. Besides, the impact of renewable power generation on scheduling is studied. In [88], the price uncertainty in the future time slots is modeled through robust optimization techniques. The robust model is transformed into a linear programming problem from which the optimal consumption level in the current time slot is solved. The objective is to achieve the minimum daily energy consumption. In [89], a multi-timescale and multi-stage power consumption scheduling framework is proposed and formulated as a constrained stochastic optimization problem. The formulation incorporates the thermal dynamics

of residential homes, temperature measurements and the real-time price signal into consideration. The objective is to minimize the customers' discomfort level and to satisfy the cost and peak power constraints. In [90], a multi-timescale power consumption scheduling problem composed of day-ahead scheduling and real-time scheduling is studied. The day-ahead scheduling is solved based on distributional information of power generation and demand. The real-time scheduling is solved based on actual information. The multi-timescale scheduling problem is formulated as a multi-timescale MDP. In [91], the power consumption scheduling algorithm is formulated as an integer linear programming problem. The decision is the amount and time of power consumption for the load. Both centralized and distributed scheduling cases are considered, where a branch and bound method is used to obtain the optimal solution.

Note that even though the term "price uncertainty" appears in some works, it only refers to the uncertainty of the future price. The current price is assumed to be observable and certain. However, this assumption may not be realistic in some circumstances when disconnection and failure happen in the data communication networks of smart grid. Very few works in the literature considered the impact of the incomplete power price information on the deferrable load scheduling performance. On the contrary, in Chapter 4, the situation where the price information may be unobservable due to data communication unavailability is considered. The deferrable scheduling policy in such a situation is obtained and compared with that obtained in a perfect connection scenario. Moreover, a POMDP based scheduling algorithm coupled with the channel selection strategy is proposed to mitigate the impact caused by incomplete power price information.

2.3 Related Works on PHEV Charging Scheduling and Power Supply Optimization in Smart Grid

PHEV Charging Scheduling

The PHEV charging scheduling problem has been studied by many papers in the literature. In [92], resilient PHEV charging policies are developed for PHEV owners with the purpose of minimizing long-term power consumption cost paid by them. It assumes that time-varying price information may be under denial-of-service (DoS) attack or falsification attack. Besides, different PHEV mobility patterns as well as multiple battery levels are included in the system model. Its scheduling results reveal the impact caused by the attacks on the power consumption cost. In [93], historical

price data are used together as a training set by the k-Nearest Neighbor (KNN) classification algorithm so that the prices in future time slot can be predicted. A decision on whether or not to charge a PHEV depends on the predicted price and the price threshold in each time slot. In [94], an optimal charging scheme was proposed for public PHEVs (e.g., taxis). A price threshold is computed for each time slot. If the time-varying price in a time slot is lower than the threshold, a PHEV is allowed to be charged. Some other papers discuss the charging scheduling problem from the perspective of charging station. In [95], an energy storage device (ESD) is deployed in a charging station. Incoming PHEVs can be either charged from the grid or charged from ESD. The performance of two charging strategies, “charge from grid first” and “charge from ESD first”, are compared in terms of blocking probability, which is the probability that an incoming PHEV cannot be served due to lack of charging resource. Besides, the effects of different energy storage technologies were also discussed in [95]. In [96], a coordinated charging scheme was designed to be used by a central controller in a public infrastructure to control the charging of PHEVs parking in it. The scheme aims to achieve a balance between mitigating the stress caused by PHEVs’ charging on power distribution systems and satisfying the charging deadlines of PHEVs. In [97], an aggregator controls the charging activities of several electric vehicles (EVs) connected with outlets in a residence or charging stations. The aggregator decides the charging rate of an EV in each hour with respect to the EV owner’s requirement such as deadline of charging and desired state of charge at plug-out time. In the formulation of the scheduling problem in [97], the historical data is obtained an estimation of an EV’s power demand in each hour. [97] also analyzed the benefit of energy storage in further saving the aggregator’s cost. In [98], the mobility behavior of EVs and location of charging points (e.g., charging stations or charging slots in parking area) was modeled as a graph. The graph is composed of edges and nodes that represent roads and junctions of roads, respectively. An EV travels from a node in the graph and may park and charge at a charging point before it reaches the end node. Based on the EV’s initial battery level, the length of charging stations with respect to the EV’s start node and end node, the availability of charging slot (e.g., outlet or chargers) in each charging points, a set of feasible charging points will be selected by an agent that may embedded in the navigation system of the EV. In [98], an allocation algorithm was proposed to allocate PHEVs to the optimal charging point with the objective to maximize the profit of EV owners, to manage traffic congestion, and to maximize the profit of the charging point owners. In [99], the Less Laxity and Longer remaining Processing time (LLLP) charging principle was proved to produce the lowest time-average cost compared with the Earliest Deadline First (EDF) principle and the Least Laxity and Shorter remaining Processing time) principle. The term “laxity” is defined as the maximum length of waiting time that a PHEV can tolerate. An infinite-horizon MDP model was formulated

for the charging scheduling problem in [99]. The objective is to minimize the time-average overall social welfare which includes the customers' utility obtained from charging service, the cost paid for power usage, and the cost of customers' dissatisfaction due to unfinished charging requests. The EV charging scheduling problem was studied from a perspective of power supply and demand balancing in [100]. The charging of EVs are controlled by power aggregator to shape the power demand of EVs and mitigate the impact of numerous EVs' charging on the distribution system of grid.

Storage devices such as supercapacitor and flywheel are also considered as auxiliary charging equipments in a fast charging station discussed in [101]. In [101], the operation of a charging station is divided in three phases. Phases 1 and 2 belongs to the PHEV battery charging period during which power from grid and storage device will be used for charging. The time period (maximum 7.5 minutes) in phase 3 is used to fully charge the storage device and PHEVs are not allowed to enter the charging station. The algorithm proposed in [101] aims to optimize the duration of each phase and the capacity of energy storage devices. In [102], an optimal charging sequence method is selected from four candidate sequence methods so as to absorb the surplus power generated by renewable sources. If the four methods have the same absorbing capability, the method that can achieve the highest customer satisfaction index (SI) will be chosen. The satisfaction index is defined as the ratio of charged energy to the required energy.

However, compared with conventional charging station, there is not many papers taking the charging station that adopts the battery replacement strategy, or so-called, battery switch station (BSS) as a studying subject. Even for papers that study the issue about BSS, some papers [103, 104] focus on analyzing the benefit that the power grid can get from BSSs when they are used cooperatively as a power storage system. Battery switch stations are assumed to absorb the surplus power generated by renewable sources through charging batteries during off-peak hours of power demand so as to fill the valley of power demand curve. In peak hours, the power in battery switch stations will be discharged from batteries and directed to the grid so that the balance between power demand and power supply can be maintained. Other papers [105, 106] propose some algorithm to find the optimal locations and capacity of battery switch stations with respect to the requirement from PHEV owners and grid operator. Different with the existing works, in our work, the battery charging scheduling problem for a battery switch station is formulated while the dynamic power price and the stochastic characteristic of PHEV's arrival process are taken into account. Optimal scheduling policies are solved and the impact of unavailability of data communication connection on the scheduling performance is evaluated quantitatively.

Power Supply Optimization

For the aspect of power supply optimization, [107] formulated the power supply optimization problem as a stochastic programming model. The scheduler decides the optimal reserved power that is fixed for all scenarios and optimal on-demand power that is used to reinforce the insufficient reserved power in each demand scenario appearing in real-time. [107] analyzes the distortion of the probability distribution caused by packet loss and the impact of distorted demand distribution on power supply cost. In [108], energy users are divided into traditional users and opportunistic users (e.g., smart appliances). The reservation of power supply is made in a day-ahead market. In real-time scheduling, [108] aims to find optimal real-time prices to control power demand of opportunistic users to mitigate the impact of the intermittent power generation of renewable sources on the grid stability. In [109], the charging agent, or so-called aggregator, signs contracts with EV owners that the owners will plug-in their EVs during nighttime only. A set of time slots that correspond to a set of the lowest forecasted reserve power prices will be chosen by the aggregator to charge an EV, according to the EV's characteristic. [110] discussed the scheduling of EV charging in a residential area during off-peak hours. The charging of EVs in each slot and the reserved power bought by aggregators from generators day-ahead is optimized jointly to achieve the minimum power consumption cost and the lowest penalty cost due to mismatch between reserved power and real-time power demand. The plug-in time period, energy demand and maximum charging rate of an EV is assumed to be stochastic and are taken into account in the scheduling problem formulation in [110].

However, none of these papers estimates the uncertainty of power demand through obtaining the power demand distribution based on the optimal policies that the scheduler of a charging station takes. As the optimal policies is affected by dynamic power price, PHEV arrival process and the requirement from PHEV owners. Under different circumstances, the optimal policies may be different. Different from existing works, in Chapter 5, an algorithm is proposed to derive the power demand distribution of several charging stations in each time period based on the scheduling policies and the charging scheduling model. Besides, renewable source as well as energy storage devices are included in the power supply optimization problem under consideration.

Chapter 3

Medium Access Control for Dynamic Spectrum Access in Cognitive Radio Networks: Analysis under Uncertainty

3.1 Introduction

Non-uniform usage of radio resource over time, location, and frequency [1] results in spectrum opportunity which can be exploited to improve the efficiency of the wireless communication system. The concept of cognitive radio which is implemented based on software defined radio was introduced to improve the utilization of the radio resource. In cognitive radio network, an unlicensed user (i.e., secondary user) can opportunistically access unoccupied channel allocated to a licensed user (i.e., primary user). This channel access scheme can be achieved using DSA at MAC layer.

In this chapter, the cognitive radio network with multiple primary and secondary users is considered. The secondary users can opportunistically access channels licensed by the primary users if the channels are sensed to be idle. A two-state Markov chain is used to model the state transitions of the licensed channels. Moreover a queueing model based on a two-dimensional discrete-time Markov chain is developed to analyze packet transmissions of the secondary users and to obtain their QoS performance measures such as average queue length, packet dropping probability, queue throughput and average delay. The actual value of each channel state transition probability is uncertain and is assumed to be in an uncertainty interval. We apply a method for manipulating the Markov chain

with uncertainty to transform the problem into a linear optimization form and obtain the lower bound and upper bound of the QoS measures under uncertainty. These lower and upper bounds can determine the performance gap when a secondary user operates in the worst and best case scenarios, respectively. The analysis under uncertainty will be useful for the design of a cognitive radio network whose system parameters cannot be determined precisely.

The rest of this chapter is organized as follows. In Section 3.2, we describe the system model and assumptions including interval uncertainty (i.e., D-norm) of channel state transition probability matrix. In Section 3.3, we first introduce the state space of system model under consideration, and then we present the procedures of obtaining the stationary probabilities of system states under uncertainty. In Section 3.4, we discuss the arrival and departure processes of the secondary system as well as the establishment procedures of system state transition matrix. In Section 3.5, the performance evaluation results of the dynamic spectrum access under the effect of uncertainty are given. The chapter is summarized in Section 3.6.

3.2 System Model and Assumptions

We consider a cognitive radio network composed of primary users and a secondary system (Fig. 3.1). The number of available channels is I and each of which is allocated to a primary user. The transmission of a primary user is time slotted. When a primary user does not transmit any data, the corresponding channel becomes idle for one time slot, and it can be accessed by the secondary system. The secondary system uses opportunistic MAC algorithm to sense and access these available channels. The secondary system has a centralized controller (e.g., access point/base station) transmitting data to S heterogeneous secondary users when idle channels are detected. Note that here although we only consider the downlink direction, the same model can be applied for the uplink direction. The state of a channel can be obtained by the secondary controller through channel sensing. We assume that the coverage area of the transmission from a primary user is much larger than that of a secondary system. Therefore, if the secondary controller detects any idle channel, that channel will be also idle at all transceivers of secondary users. At the secondary controller, a separate queue is used to buffer arriving packets for each secondary user, and a round-robin packet scheduler is employed to control the packet transmission from different queues. A secondary controller has F interfaces, and each of these interfaces can sense and access idle channel independently. In each time slot, when several channels are sensed to be idle by the same amount of interfaces separately,

these interfaces will access their corresponding idle channels and transmit packets cooperatively from only one of the queues according to the order defined by the round-robin rule. Because the interfaces are managed by the secondary controller, the secondary controller can synchronize the packet transmissions of these interfaces and ensure the cooperation among them. Moreover, the transmission of each interface on the idle channel is based on adaptive modulation and coding to enhance the transmission rate if channel quality permits. The details regarding the channel sensing algorithm of the interfaces will be elaborated in the subsection 3.2.2.

Figure 3.1: System model for dynamic spectrum access in a cognitive radio network.

Note that this system model is compatible with an IEEE 802.22-based wireless regional area network (WRAN). In this system, the primary user is the TV service. The secondary system is WRAN, and the secondary controller is IEEE 802.22 base station. This base station transmits data to the WRAN users (i.e., secondary users) in the downlink direction when the TV band is not occupied by TV service.

3.2.1 Channel Characteristics

The state of a channel allocated to a primary user can be idle or occupied. The ‘idle’ state means that in the present time slot the channel is not used by the corresponding primary user and can be sensed and used by a secondary user. The ‘occupied’ state means that in the present time slot the corresponding primary user is transmitting packets over the channel. The channel state transition

matrix for channel l can be represented as follows:

$$\mathbf{C}_l = \begin{bmatrix} C_{0,0}(l) & C_{0,1}(l) \\ C_{1,0}(l) & C_{1,1}(l) \end{bmatrix}, \quad (3.1)$$

where 0 and 1 represent ‘idle’ and ‘occupied’ states, respectively. For example, $C_{0,0}(l)$ represents the transition probability from ‘idle’ state in current time slot to ‘idle’ state in next time slot of channel l .

To improve the performance of the secondary system, adaptive modulation and coding is used for the transmission. We consider Nakagami- m channel model for the transmission between the secondary controller and the secondary users. The channel quality of this transmission is determined by the instantaneous received signal-to-noise ratio (SNR) γ . With adaptive modulation, the SNR at the receiver is divided into $R + 1$ non-overlapping intervals by thresholds Γ_r ($r \in \{1, \dots, R\}$) where $0 = \Gamma_0 < \Gamma_1 < \dots < \Gamma_{R+1} = \infty$. The transmission mode r is used if $\Gamma_r \leq \gamma < \Gamma_{r+1}$. To avoid possible transmission error, no packet is transmitted when $\gamma < \Gamma_1$. With Nakagami- m fading, the probability of using transmission mode r (i.e., $\Pr(r)$) is given by [112]

$$\Pr(r) = \frac{\Gamma(m, m\Gamma_r/\bar{\gamma}) - \Gamma(m, m\Gamma_{r+1}/\bar{\gamma})}{\Gamma(m)}, \quad (3.2)$$

where $\bar{\gamma}$ is the average SNR, m is the Nakagami fading parameter ($m \geq 0.5$), $\Gamma(m)$ is the Gamma function, and $\Gamma(m, \gamma)$ is the complementary incomplete Gamma function [113].

3.2.2 Transmission of Secondary System

For the secondary system, the secondary controller senses the target channel and accesses if it is idle. Otherwise, the secondary controller continues sensing other channels until an idle channel is found or all channels are sensed to be occupied. We assume that an order of channel sensing is fixed and defined as a channel sensing policy. This channel sensing policy is denoted by $\mathbf{l} = [l_1 \ \dots \ l_i \ \dots \ l_I]$ where l_1 and l_I are the first and the last channels to be sensed, respectively. If the secondary controller has multiple interfaces, each interface will be assigned to sense a different channel from channel sensing policy $\mathbf{l}$ at the same time.

For the secondary system, one time slot is divided into M mini-slots. The size of each mini-slot is equal to the time interval required to perform channel sensing. The channel sensing algorithm

performed in each mini-slot is shown in Algorithm 1. This channel sensing algorithm is performed at the beginning of a time slot (i.e., the first mini-slot). If a channel is sensed to be occupied, the secondary controller will skip accessing that channel and perform sensing on the next channel according to the channel sensing policy $\mathbf{l}$. Because of the channel sensing mechanism, the secondary system cannot utilize idle channels for an entire time slot, and this is considered to be an overhead from channel sensing.

The overhead due to channel sensing of interface f is denoted by $o_f \in \{1, \dots, M\}$ mini-slots. This overhead can be computed from Algorithm 1. For example, the secondary controller has two interfaces, and there are four channels where channels 1 and 4 are occupied whereas channels 2 and 3 are idle. The channel sensing policy is $\mathbf{l} = [1, 2, 3, 4]$. At the first mini-slot in a particular time slot, interface 1 of the secondary controller senses occupied channel 1 whereas interface 2 senses idle channel 2. As a result, channel 2 is assigned to interface 2, and this interface starts to transmit data in the second mini-slot. On the other hand, interface 1 cannot access channel 1 and proceeds to sense channel 3 which is idle in the second mini-slot. In this case, channel 3 is assigned to interface 1, and this interface starts to transmit data in the third mini-slot. The overhead due to channel sensing is $o_1 = 2$ and $o_2 = 1$, because interfaces 1 and 2 spend two and one mini-slots to sense the channels before transmitting data, respectively. Note that the length of transmission in the time slot for interfaces 1 and 2 are $M - o_1$ and $M - o_2$, respectively.

Algorithm 1 Channel Sensing Algorithm

```

1:  $i = 1$  and  $o_f = 0$  for all  $f$  {Initialize channel index and sensing overhead of each interface}
2: repeat
3:   for all Interface  $f$  do
4:     if Interface  $f$  is not assigned any channel to transmit then
5:       Sense channel  $l_i$  by interface  $f$ 
6:       if channel  $l_i$  is idle then
7:         Assign channel  $l_i$  to interface  $f$  for transmission
8:       else
9:          $o_f \leftarrow o_f + 1$  {If channel is detected to be occupied, overhead due to sensing increases}
10:      end if
11:       $i \leftarrow i + 1$  {Perform sensing on the next channel in channel sensing policy  $\mathbf{l}$ }
12:    end if
13:  end for
14: until  $i > I$  or all interfaces are assigned with the channels for transmission

```

For the transmission of the secondary controller, one packet can be transmitted with the basic modulation and coding mode $r = 1$ in a mini-slot. Therefore, in one time slot, the number of packets

to be transmitted by interface f is $\lfloor b_r/b_1(M - o_f) \rfloor$ where b_r is the number of information bits per symbol corresponding to transmission mode r . We assume that for each interface, the same transmission mode (i.e., modulation scheme and coding rate) is used in all mini-slots of the same time slot by the secondary controller.

Because the secondary system serves multiple secondary users, a round-robin packet scheduler is employed at the secondary controller. With this scheduler, each time slot is allocated for the transmission to each secondary user.

3.2.3 Uncertainty

Because of estimation error and noise, the parameters (e.g., state transition probabilities of channel) of the cognitive radio network cannot be determined precisely. This uncertainty has to be taken into account when performing analysis on the aforementioned system model. In particular, the actual values of the system parameters are in an uncertainty region. Here we assume that the uncertainty region follows a “D-norm” pattern, which means that the actual value exists in an interval. For example, the state transition matrix of channel l is defined by $\mathbf{C}_l^- \leq \mathbf{C}_l \leq \mathbf{C}_l^+$ where $\mathbf{C}_l^-$ and $\mathbf{C}_l^+$ are the lower and upper bound matrices of $\mathbf{C}_l$ which are defined as follows:

$$\mathbf{C}_l^- = \begin{bmatrix} C_{0,0}^-(l) & C_{0,1}^-(l) \\ C_{1,0}^-(l) & C_{1,1}^-(l) \end{bmatrix}, \text{ and } \mathbf{C}_l^+ = \begin{bmatrix} C_{0,0}^+(l) & C_{0,1}^+(l) \\ C_{1,0}^+(l) & C_{1,1}^+(l) \end{bmatrix}. \quad (3.3)$$

In other words, we have $C_{0,0}^-(l) \leq C_{0,0}(l) \leq C_{0,0}^+(l)$, $C_{0,1}^-(l) \leq C_{0,1}(l) \leq C_{0,1}^+(l)$, $C_{1,0}^-(l) \leq C_{1,0}(l) \leq C_{1,0}^+(l)$, and $C_{1,1}^-(l) \leq C_{1,1}(l) \leq C_{1,1}^+(l)$. In the following example, we will show how to derive the lower bound $\mathbf{C}_l^-$ and upper bound $\mathbf{C}_l^+$.

We assume that the secondary controller has maintained a record for the channel sensing results in each time slot for a certain period of time (e.g., a few minutes). The length of this observation period is denoted by T , which can be divided into s time segments $\{t_1, t_2, \dots, t_i, \dots, t_s\}$, where i is an index of time segment. The secondary controller can analyze the channel sensing results and obtain the transition probabilities of channel l (i.e., $C_{0,0}(l)$, $C_{0,1}(l)$, $C_{1,0}(l)$, and $C_{1,1}(l)$). Let the number of times for the corresponding state transitions be denoted by $n_l^i(0, 0)$, $n_l^i(0, 1)$, $n_l^i(1, 0)$, and $n_l^i(1, 1)$ for time segment t_i . Also, let $\hat{C}_{0,0}^i(l)$, $\hat{C}_{0,1}^i(l)$, $\hat{C}_{1,0}^i(l)$, and $\hat{C}_{1,1}^i(l)$ denote the estimated transition probabilities of $C_{0,0}(l)$, $C_{0,1}(l)$, $C_{1,0}(l)$, and $C_{1,1}(l)$ for time segment t_i , respectively. With the estimation algorithm proposed in [111] for channel state transition probability, the esti-

mated channel state transition probabilities $\hat{C}_{0,1}^i(l)$ and $\hat{C}_{1,0}^i(l)$ can be obtained as follows:

$$\begin{cases} \hat{C}_{0,1}^i(l) = \frac{n_l^i(0, 1)}{n_l^i(0, 0) + n_l^i(0, 1)} \\ \hat{C}_{1,0}^i(l) = \frac{n_l^i(1, 0)}{n_l^i(1, 0) + n_l^i(1, 1)}. \end{cases} \quad (3.4)$$

From $\hat{C}_{0,1}^i(l)$ and $\hat{C}_{1,0}^i(l)$, we can obtain the estimated transition probabilities $\hat{C}_{0,0}^i(l)$ and $\hat{C}_{1,1}^i(l)$ for time segment t_i as follows:

$$\begin{cases} \hat{C}_{0,0}^i(l) = 1 - \hat{C}_{0,1}^i(l) \\ \hat{C}_{1,1}^i(l) = 1 - \hat{C}_{1,0}^i(l). \end{cases} \quad (3.5)$$

For all time segments $\{t_1, t_2, \dots, t_i, \dots, t_s\}$, we can obtain the sequence $\{\hat{C}_{0,1}^1(l), \hat{C}_{0,1}^2(l), \dots, \hat{C}_{0,1}^i(l), \dots, \hat{C}_{0,1}^s(l)\}$ for the transition probability $\hat{C}_{0,1}^i(l)$. Similar sequences of samples can also be obtained for transition probabilities $\hat{C}_{0,0}^i(l)$, $\hat{C}_{1,0}^i(l)$, and $\hat{C}_{1,1}^i(l)$. Then, the mean value and the standard deviation of the elements in a sequence can be used to estimate the upper and lower bounds of the channel state transition probability.

Take the transition probability $\hat{C}_{0,1}^i(l)$ for an example. The mean value and the standard deviation of the elements in the sequence for $\hat{C}_{0,1}^i(l)$ can be calculated as follows:

$$\mu_{0,1}(l) = \frac{\sum_{t=1}^s \hat{C}_{0,1}^t(l)}{s}, \quad \sigma_{0,1}(l) = \sqrt{\frac{1}{s} \sum_{t=1}^s (\hat{C}_{0,1}^t(l) - \mu_{0,1}(l))^2}, \quad (3.6)$$

where $\mu_{0,1}(l)$ denotes the mean value of $\hat{C}_{0,1}^i(l)$, and $\sigma_{0,1}(l)$ denotes the standard deviation.

Then, let the confidence interval of the samples of $\hat{C}_{0,1}^i(l)$ be defined as $[\mu_{0,1}(l) - k\sigma_{0,1}(l), \mu_{0,1}(l) + k\sigma_{0,1}(l)]$. k is the confidence coefficient which should be set appropriately to reflect the observer's confidence on the reasonable range of the samples' values. Afterward, the lower bound of the transition probability $C_{0,1}(l)$ is obtained as: $C_{0,1}^-(l) = \max\{\mu_{0,1}(l) - k\sigma_{0,1}(l), \hat{C}_{0,1}^{\min}(l)\}$, where $\hat{C}_{0,1}^{\min}(l) = \min\{\hat{C}_{0,1}^1(l), \hat{C}_{0,1}^2(l), \dots, \hat{C}_{0,1}^i(l), \dots, \hat{C}_{0,1}^s(l)\}$.

The upper bound of $C_{0,1}(l)$ is obtained as: $C_{0,1}^+(l) = \min\{\mu_{0,1}(l) + k\sigma_{0,1}(l), \hat{C}_{0,1}^{\max}(l)\}$, where $\hat{C}_{0,1}^{\max}(l) = \max\{\hat{C}_{0,1}^1(l), \hat{C}_{0,1}^2(l), \dots, \hat{C}_{0,1}^i(l), \dots, \hat{C}_{0,1}^s(l)\}$.

In the same way, the upper bounds and lower bounds of the transition probabilities $C_{0,0}(l)$, $C_{1,0}(l)$, and $C_{1,1}(l)$ can also be obtained.

3.3 State Space Formulation and Stationary Probabilities Calculation under Uncertainty

In this section, firstly the state space of system model under consideration is introduced, then the stationary probabilities of system states under uncertainty are solved by using a robust optimization method. The QoS measures of the system such as packet dropping probability, queue throughput and average delay can be derived from the stationary probabilities obtained under uncertainty as shown in the Section 3.5.

3.3.1 State Space

The DTMC is used to model the queueing behavior at the radio-link level of each queue managed by the secondary controller for each secondary user. This queueing model is developed for each secondary user. In addition, the performance of the entire system can also be derived from this model. We assume that the state of the queue corresponding to a particular secondary user is observed at the end of each time slot. In this case, the packet arrived in time slot t will be transmitted in time slot $t + 1$ as the earliest. The state space of this Markov chain can be defined as follows:

$$\Psi = \{(X, C, \mathcal{U}); X \in \{0, 1, \dots, X\}, \mathcal{U} \in \{1, \dots, S\}\}, \quad (3.7)$$

where X , C , and $\mathcal{U}$ are the random variables representing the number of packets in queue, the states of licensed channels, and the index of the secondary user assigned by the round-robin scheduler to transmit data in the current time slot, respectively. Here, X is the maximum queue size and S is the total number of secondary users served by the secondary controller. Because there are multiple primary users and their channel accessing behaviors are independent, the random variable representing the states of channels can be expressed as follows:

$$C = \bigcup_{i=1}^I C_{l_i}, \quad C_{l_i} \in \{0, 1\}, \quad (3.8)$$

where C_{l_i} is the random variable representing the state of channel l_i in the channel sensing policy. Note that $C_{l_i} = 0$ and $C_{l_i} = 1$ indicate the channel l_i is idle and occupied by the corresponding primary user, respectively.

The transition matrix $\mathbf{P}$ of the system states can be established from the packet arrival probability,

the transmission probability, the channel state transition matrix and the round-robin state transition matrix. In the following subsection, we will derive the stationary probabilities under uncertainty from the system state transition matrix $\mathbf{P}$ and leave the details of the establishment procedures to be discussed in Section 3.4.

3.3.2 Solving Stationary Probabilities under Uncertainty by Using Robust Optimization Method

Because of noise and estimation error, the value of each element in channel state transition matrix may not be certain as explained in Section 3.2. We assume that the actual value varies in an interval (i.e., D-norm). The lower and upper bound transition probability matrices are denoted by $\mathbf{C}_l^-$ and $\mathbf{C}_l^+$, respectively, for the uncertainty of channel l . These matrices are defined as those in (3.3). Because the states combination of all channels licensed by primary users constitutes one of the three factors of the system state space as defined in (3.7), the uncertainty of the state transition matrices of all channels will finally result in the uncertainty of system state transition matrix $\mathbf{P}$. Following the establishment procedures of matrix $\mathbf{P}$ which will be described in the later section, the lower and upper bounds of system state transition matrices resulting from the uncertainty of the state transition matrices of all channels can be obtained. The lower and upper bounds of system state transition matrices are denoted by $\mathbf{P}^-$ and $\mathbf{P}^+$, respectively.

The stationary probability of the system state defined in (3.7) is denoted by π_ι for nominal value, and π_ι^- and π_ι^+ for the lower and upper bounds of state $\iota \in \Psi$, respectively. To obtain the stationary probability (i.e., nominal value, lower and upper bounds) of a Markov chain with uncertainty, the following optimization problem can be defined:

$$\min_{\vec{\pi}, \Theta} \quad \vec{v}^T \vec{\pi}, \quad (3.9)$$

$$\text{subject to} \quad \Theta \in \mathbb{U}, \quad (3.10)$$

$$\vec{1}^T \Theta = \vec{0}^T, \quad \Theta \vec{\pi} = \vec{0}, \quad (3.11)$$

$$\vec{1}^T \vec{\pi} = 1, \quad \vec{\pi} \geq \vec{0}, \quad (3.12)$$

where $\mathbb{U}$ is the uncertainty set of matrix Θ . $\vec{1}$ is a vector of ones and $\vec{1}^T$ is the transpose of $\vec{1}$. $\vec{v}^T$ is a row vector and the transpose of vector $\vec{v}$. $\vec{v}$ contains the objective coefficients and is defined as $\vec{v} = \vec{e}_\iota$, where $\vec{e}_\iota$ is the unit vector (i.e., all elements are zeros except that the row corresponding to state ι will be one) when we want to obtain the lower bound for the stationary probability of state ι ,

or $\vec{v}$ is defined as $\vec{v} = \vec{1} - \vec{e}_\iota$ when we want to obtain the upper bound for the stationary probability of state ι . $\vec{\pi}$ is a vector of stationary probabilities (e.g., π_ι). $\Theta = \mathbf{I} - \mathbf{P}^T$ and $\mathbf{I}$ is the identity matrix. Let $\theta_{\iota,\iota'}$ denote the element of matrix Θ corresponding to states ι and ι' . The off-diagonal element of matrix Θ must be non-positive, i.e., $\theta_{\iota,\iota'} \leq 0$, for $\iota \neq \iota'$ and $\iota, \iota' \in \Psi$. The diagonal elements must be bounded by one, i.e., $\theta_{\iota,\iota} \leq 1$ for $\iota \in \Psi$.

Let $p_{\iota,\iota'}^-$ and $p_{\iota,\iota'}^+$ denote, respectively, the lower and upper bounds on the transition probability of the Markov chain. That is, $p_{\iota,\iota'}^-$ and $p_{\iota,\iota'}^+$ are the elements corresponding to the current state ι and the next state ι' of matrices $\mathbf{P}^-$ and $\mathbf{P}^+$, respectively. The corresponding lower and upper bounds of the elements of the matrix Θ can be obtained from $\theta_{\iota,\iota'}^- = -p_{\iota',\iota}^+$ and $\theta_{\iota,\iota'}^+ = -p_{\iota',\iota}^-$, where $\theta_{\iota,\iota'}^- \leq \theta_{\iota,\iota'} \leq \theta_{\iota,\iota'}^+$ for $\iota \neq \iota'$ and $\iota, \iota' \in \Psi$. Therefore, the conditions for the upper and lower bounds of the elements of the matrix Θ are as follows:

- For off-diagonal element, $-1 \leq \theta_{\iota,\iota'}^- \leq \theta_{\iota,\iota'}^+ \leq 0$ for $\iota \neq \iota'$ and $\iota, \iota' \in \Psi$.
- For diagonal element, $0 < \theta_{\iota,\iota}^- \leq \theta_{\iota,\iota}^+ \leq 1$ for $\iota \in \Psi$.
- For all elements with $\iota' \in \Psi$, $\sum_{\iota \in \Psi} \theta_{\iota,\iota'}^- \leq 0$ and $\sum_{\iota \in \Psi} \theta_{\iota,\iota'}^+ \geq 0$.

With the interval uncertainty set $\mathbb{U}$, the constraint in (3.10) becomes

$$\Theta^- \leq \Theta \leq \Theta^+, \quad (3.13)$$

where Θ^- and Θ^+ are matrices of lower bound $\theta_{\iota,\iota'}^-$ and upper bound $\theta_{\iota,\iota'}^+$, respectively. By letting

$$\xi_{\iota'} = \pi_{\iota'} \theta_{\iota'}, \quad (3.14)$$

where $\theta_{\iota'}$ is the ι' th column of matrix Θ , and $\xi_{\iota'}$ is the ι' th column of the introduced matrix Ξ , then the equivalent linear programming problem with the objective defined in (3.9) and the constraints defined in (3.11), (3.12), and (3.13) can be expressed as follows [78]:

$$\begin{aligned} \min_{\vec{\pi}, \Xi} \quad & \vec{v}^T \vec{\pi}, \\ \text{subject to} \quad & \pi_{\iota'} \theta_{\iota,\iota'}^- \leq \xi_{\iota,\iota'} \leq \pi_{\iota'} \theta_{\iota,\iota'}^+, \quad \iota, \iota' \in \Psi, \\ & \vec{1}^T \Xi = \vec{0}^T, \quad \Xi \vec{1} = \vec{0}, \\ & \vec{1}^T \vec{\pi} = 1, \quad \vec{\pi} \geq \vec{0}, \end{aligned} \quad (3.15)$$

where $\xi_{\iota,\iota'}$ is the element of matrix Ξ . As mentioned previously, π_{ι}^{-} and π_{ι}^{+} denote the smallest and largest possible values (i.e., lower and upper bounds) for the stationary probability of state ι , and the corresponding stationary probability vectors are denoted by $\vec{\pi}^{-}$ and $\vec{\pi}^{+}$, respectively. π_{ι}^{-} can be obtained by solving the optimization problem defined in (3.15) with the objective coefficient vector $\vec{v} = \vec{e}_{\iota}$. For π_{ι}^{+} , the objective coefficient vector is $\vec{v} = \vec{1} - \vec{e}_{\iota}$. The nominal value of the stationary probability vector denoted as $\vec{\pi}$ is obtained by solving $\vec{\pi}^T \mathbf{P} = \vec{\pi}^T$ and $\vec{\pi}^T \vec{1} = 1$. In particular, the nominal value of stationary probability π_{ι} of state $\iota \in \Psi$ is the element of vector $\vec{\pi}$. The feature of the transformation from the original robust optimization problem to the linear optimization problem is mainly specified by equation (3.14). Through equation (3.14), the uncertainty of the matrix Θ is transferred to a set of indifferent variables such as $\xi_{\iota,\iota'}$, and in this way, the problem becomes linear.

The nominal value, lower and upper bounds of stationary probabilities (i.e., π_{ι} , π_{ι}^{-} , and π_{ι}^{+} , respectively) obtained here can be used to further analyze the impact of the uncertainty in the channel state transition probabilities on the performance measures of the secondary system, which will be discussed thoroughly in Section 3.5.

3.4 Queueing Analysis

In this section, the queueing model based on the DTMC is presented for a tagged secondary user. The same model with different parameters can be used for a heterogeneous secondary user in the cognitive radio network. First, the packet arrival and transmission probabilities are derived. Then together with the state transition matrices of all channels, the establishment procedures of the system state transition matrix $\mathbf{P}$ are given. At the end of this section, we briefly discuss the impact of channel sensing error on the transmission probabilities.

3.4.1 Arrival Probability

The packet arrival process is modeled as a batch Markovian arrival process (BMAP). The BMAP is associated with a Y -phase Markov chain, and the probability of packet arrival depends on the phase. A BMAP can be represented by matrix $\mathbf{A}_a$ (where $a \in \{0, 1, \dots, A\}$) which is the transition probability matrix corresponding to the arrival of a packets and A denotes the maximum arrival batch size. In particular, the element at row y and column y' for $y, y' \in \{1, \dots, Y\}$ of matrix $\mathbf{A}_a$ denotes the probability of a arriving packets when the phase of the BMAP changes from y in the

current time slot to y' in the next time slot. We can obtain the average packet arrival rate from

$$\bar{\lambda} = \sum_{a=1}^A a \left(\vec{\alpha}^T \mathbf{A}_a \vec{1} \right), \quad (3.16)$$

where $\vec{\alpha}$ is obtained by solving $\vec{\alpha}^T \mathbf{A} = \vec{\alpha}^T$ and $\vec{\alpha}^T \vec{1} = 1$, $\mathbf{A} = \sum_{a=0}^A \mathbf{A}_a$.

3.4.2 Transmission Probability

Given the probability of using transmission mode r by interface f on channel l_i (i.e., $\text{Pr}_{l_i}(r)$), the total number of mini-slots M per time slot, and the sensing overhead o_f , we define matrix $\mathbf{D}_{f,k}$ whose diagonal elements $D_{c,c}^{(f,k)}$ correspond to the probabilities of transmitting k packets ($k = \{0, 1, \dots, K_f\}$) using interface f in one time slot as follows:

$$\mathbf{D}_{f,k} = \begin{bmatrix} D_{0,0}^{(f,k)} & & \\ & D_{1,1}^{(f,k)} & \\ & & \ddots \end{bmatrix}, \quad (3.17)$$

where K_f is the maximum number of packets that can be transmitted by interface f of the secondary controller. This K_f can be obtained from $K_f = \lfloor b_{R_f}/b_1(M - o_f) \rfloor$, where R_f is the highest transmission mode of interface f . Note that $c = 0$ and $c = 1$ correspond to the idle and occupied states of channel l_i , respectively. When the channel is idle, the element of this matrix $\mathbf{D}_{f,k}$ is obtained from

$$D_{0,0}^{(f,k)} = \text{Pr}_{l_i}(r), \quad \text{where } k = \lfloor b_r/b_1(M - o_f) \rfloor, \quad (3.18)$$

for $r = \{1, \dots, R_f\}$ where again interface f is allocated with channel l_i . The case of $r = 0$ corresponds to $D_{0,0}^{(f,0)}$ (i.e., no packet is transmitted by interface f) which can be obtained from $D_{0,0}^{(f,0)} = 1 - \sum_{k=1}^{K_f} D_{0,0}^{(f,k)}$. When a channel is occupied, this element can be obtained from

$$D_{1,1}^{(f,k)} = \begin{cases} 0, & k \in \{1, \dots, K_f\} \\ 1, & k = 0. \end{cases} \quad (3.19)$$

3.4.3 Transition Matrix

The state transition matrix $\mathbf{P}$ for the radio-link level queue of a secondary user can be expressed as in (3.20).

$$\mathbf{P} = \begin{bmatrix} \mathbf{P}_{0,0} & \cdots & \cdots & \mathbf{P}_{0,A} \\ \vdots & \ddots & \ddots & \ddots \\ \mathbf{P}_{K,0} & \cdots & \mathbf{P}_{K,K} & \cdots & \mathbf{P}_{K,K+A} \\ & \ddots & \ddots & \ddots & \ddots \\ & \mathbf{P}_{x,x-K} & \cdots & \mathbf{P}_{x,x} & \cdots & \mathbf{P}_{x,x+A} \\ & & \ddots & \ddots & \ddots & \ddots \\ & & & \mathbf{P}_{X,X-K} & \cdots & \mathbf{P}_{X,X} \end{bmatrix}. \quad (3.20)$$

The row of matrix $\mathbf{P}$ represents the number of packets in the queue. The matrix $\mathbf{p}_{x,x'}$ represents the transition probability from state x to x' , i.e., when there are x packets in the current time slot and x' packets in the next time slot. To obtain this matrix $\mathbf{p}_{x,x'}$, we start by deriving the transition matrix for the states of channels (i.e., $\mathbf{C}$). Then, the transition matrix for the secondary user assigned to a time slot by round-robin scheduler (i.e., $\mathbf{U}$) is obtained.

Because the channel accessing behavior of primary users are independent from each other, matrix $\mathbf{C}$ containing probabilities of transition between different composite states of channels can be defined as follows:

$$\mathbf{C} = \mathbf{C}_{l_1} \otimes \mathbf{C}_{l_2} \otimes \cdots \otimes \mathbf{C}_{l_{I-1}} \otimes \mathbf{C}_{l_I}, \quad (3.21)$$

where $\otimes$ is a Kronecker product. In this case, matrix $\mathbf{C}$ has size 2^I , and each row corresponds to the idle/occupied states of all channels.

Because the transmission of all interfaces at the secondary controller is independent, the transmission probability matrices for two interfaces f and f' can be obtained from

$$\mathbf{D}_{k+1} = \sum_{j=0}^k \mathbf{D}_{f,j} \otimes \mathbf{D}_{f',k-j}, \quad (3.22)$$

for $k = 0, 1, \dots, K_f + K_{f'} - 1$. Note that the maximum number of packets that can be transmitted by the secondary controller using all interfaces in one time slot is K which is obtained from

$$K = \sum_{f=1}^F \lfloor b_{R_f} / b_1 (M - 1) \rfloor. \quad (3.23)$$

The operation in (3.22) is performed for $f = \{1, \dots, F\}$.

With the round-robin scheduler, secondary users are assigned to each time slot sequentially and in a circular fashion. Let matrix $\mathbf{U}$ denote the transition matrix containing transference probabilities of

time slot usage right between any two secondary users. The element of this matrix $\mathbf{U}$ is denoted by $U_{u,u'}$ for row u (i.e., the secondary user u is assigned to the current time slot) and column u' (i.e., the secondary user is assigned to the next time slot) where the $u, u' \in \{1, \dots, S\}$. This element can be determined from

$$U_{u,u'} = \begin{cases} 1, & u' = u + 1 \text{ or } u = S, u' = 1 \\ 0, & \text{otherwise.} \end{cases} \quad (3.24)$$

The size of this matrix $\mathbf{U}$ is $S \times S$ (S is the total number of secondary users in the secondary system). Note that because the transitions of the channel state and the secondary user assigned to a time slot are independent, the transition matrices can be combined as $\mathbf{U} \otimes \mathbf{C}$. The row of resulting matrix corresponds to the channel states and the secondary user assigned to the time slot.

Next, we construct the transmission probability matrix $\mathbf{T}_k$ in order to be coordinated with the transition of the channel states and the secondary user assigned to a time slot. This matrix $\mathbf{T}_k$ has size $S2^I \times S2^I$, where the diagonal element corresponds to the probability that $k \in \{0, 1, \dots, K\}$ packets are transmitted. This matrix can be obtained from

$$\mathbf{T}_0 = \begin{bmatrix} \mathbf{D}_0 & \\ & \mathbf{I} \end{bmatrix}, \quad \mathbf{T}_k = \begin{bmatrix} \mathbf{D}_k & \\ & \mathbf{0} \end{bmatrix}, \quad (3.25)$$

where $\mathbf{I}$ is the identity matrix and $\mathbf{0}$ is the matrix of zeros. In this case, there is no packet transmission if another secondary user is assigned to the time slot by a round-robin scheduler. Note that $\mathbf{I}$ and $\mathbf{0}$ in (3.25) have the same size of $(S-1)2^I \times (S-1)2^I$.

Then, element $\mathbf{p}_{x,x'}$ in (3.20) can be obtained by combining arrival probability with transmission probability matrices as follows:

$$\mathbf{p}_{x,x-w} = \sum_{\{k,a|k-a=w\}} \mathbf{A}_a \otimes (\mathbf{C} \otimes \mathbf{U} \times \mathbf{T}_k), \quad (3.26)$$

$$\mathbf{p}_{x,x+v} = \sum_{\{k,a|a-k=v\}} \mathbf{A}_a \otimes (\mathbf{C} \otimes \mathbf{U} \times \mathbf{T}_k), \quad (3.27)$$

$$\mathbf{p}_{x,x} = \sum_{\{k,a|a=k\}} \mathbf{A}_a \otimes (\mathbf{C} \otimes \mathbf{U} \times \mathbf{T}_k), \quad (3.28)$$

for $w = 1, \dots, K'$ and $v = 1, \dots, A$, where $k \in \{0, 1, 2, \dots, K'\}$ and $a \in \{0, 1, 2, \dots, A\}$ represent the number of transmitted packets and arriving packets, respectively. $K' = \min(K, x)$ indicates the maximum number of packets that can be transmitted. This number K' depends on K and the number of packets in the queue x .

3.4.4 Channel Sensing Error

Because of noise and randomness of channels, the result obtained from channel sensing performed by the secondary controller can be incorrect. This is referred to as channel sensing error. There are two types of sensing error, i.e., false-positive error and false-negative error. In false-positive sensing error, an idle channel is sensed to be occupied. As a result, this idle channel is not accessed by the secondary controller. In false-negative sensing error, an occupied channel is sensed to be idle. As a result, the secondary controller transmits data and a collision with the transmission of a primary user occurs. We assume that the false-positive and false-negative sensing errors of channel l occur with probabilities $P_{fp}^{(l)}$ and $P_{fn}^{(l)}$, respectively.

These sensing errors will affect the packet transmission from the queue of a secondary user. In particular, false-positive sensing error increases the overhead o_f while false-negative sensing error results in waste of an entire time slot for the secondary system due to collision. In the queueing model, these errors affect the transmission probability matrices. Let us consider the case of single interface (i.e., $f = 1$) and I channels. The probability of correct channel sensing which results in successful channel access by the secondary controller is given by

$$P_{suc}(o_f=l_i)=\begin{cases} (\prod_{i'=1}^{i-1} \mathcal{P}(l_{i'}))(1-P_{fp}^{(l_i)}), & C_{l_i}=0, \\ 0, & \text{otherwise,} \end{cases} \quad (3.29)$$

for $i \in \{1, \dots, I\}$, where

$$\mathcal{P}(l_{i'}) = \begin{cases} 1 - P_{fn}^{(l_{i'})}, & C_{l_{i'}} = 1 \\ P_{fp}^{(l_{i'})}, & C_{l_{i'}} = 0. \end{cases} \quad (3.30)$$

For an example of $\mathbf{l} = [1, 2, 3, 4]$ and $C_1 = 0$, $C_2 = 1$, $C_3 = 0$, and $C_4 = 1$ (i.e., channels 1 and 3 are idle whereas channels 2 and 4 are occupied), there are two possible cases which are $o_f = 1$ and $o_f = 3$ (i.e., the sensing overhead is 1 or 3, respectively). Because an interface senses channels in a sequential order, channel 1 is the first channel sensed by the interface. Therefore, the probability of $o_f = 1$ equals to the probability that channel 1 is correctly sensed. It can be calculated as: $P_{suc}(o_f = 1) = (1 - P_{fp}^{(1)})$ (i.e., false-positive error does not occur when channel 1 is sensed). $o_f = 3$ only happens when channel 1 is not correctly sensed, channel 2 is correctly sensed to be occupied, and channel 3 is correctly sensed to be idle. Hence, the probability of $o_f = 3$ is calculated as: $P_{suc}(o_f = 3) = P_{fp}^{(1)}(1 - P_{fn}^{(2)})(1 - P_{fp}^{(3)})$ (i.e., false-positive error occurs when channel 1 is sensed, false-negative error does not occur when channel 2 is sensed, and false-positive error does

not occur when channel 3 is sensed).

Let the transmission probability matrix $\mathbf{D}_{f,k}$ in (3.17) be defined as a function of overhead due to sensing as $\mathbf{D}_{f,k}(o_f)$. The transmission probability matrix $\tilde{\mathbf{D}}_{f,k}$ which captures channel sensing error can be defined as follows:

$$\tilde{\mathbf{D}}_{f,k} = \sum_{\{o_f | P_{suc}(o_f=l_i) > 0\}} \mathbf{D}_{f,k}(o_f) P_{suc}(o_f = l_i), \quad (3.31)$$

for $k \in \{1, \dots, K_f\}$. That is, the transmission probability matrix is weighted by the probability of correct channel sensing. For the case of no packet transmission, this transmission probability matrix becomes

$$\tilde{\mathbf{D}}_{f,0} = \mathbf{I} - \sum_{k=1}^{K_f} \tilde{\mathbf{D}}_{f,k}. \quad (3.32)$$

This matrix $\tilde{\mathbf{D}}_{f,k}$ is then used by the queueing model formulation, i.e., as in (3.25).

Note that the procedure to capture channel sensing error in the queueing model with an arbitrary number of interfaces is similar to the above formulation. However, in this case, it is difficult to obtain a closed-form expression as in (3.29) and (3.30) which are for the case of single interface.

3.5 Performance Evaluation

In this section, firstly, the QoS measures for system performance evaluation are introduced, and then we configure the parameter settings of the system. From the developed theoretical model, some numerical results are obtained.

3.5.1 Quality-of-Service Measures

Given the nominal value, lower and upper bounds of stationary probability (i.e., π_ℓ , π_ℓ^- , and π_ℓ^+ , respectively), various performance measures of a secondary user can be obtained.

Average Queue Length

The average queue length is the mean number of packets in a queue. It can be obtained as follows:

$$\bar{x} = \sum_{x=1}^X x \left(\sum_{c=1}^{2^I} \sum_{u=1}^S \pi(x, c, u) \right). \quad (3.33)$$

$\pi(x, c, u)$ represents the stationary probability of the state specified by the factors x , c and u , where x represents the number of packets in a queue, c represents the composite state of channels and u represents the index of the secondary user currently transmitting data. The nominal value of the average queue length and other performance measures can be calculated by using the stationary probability vector obtained from the system state transition matrix that contains nominal transition probabilities. From (3.15), for each state ι in the state space Ψ , the stationary probability vectors that contains the upper bound and lower bound of the state ι 's stationary probability can be obtained, respectively. Based on those stationary probability vectors obtained for all states, the lower bound and the upper bound of the average queue length can be obtained.

Packet Dropping Probability

It refers to the probability that an incoming packet will be dropped because of insufficient buffer space at the transmitter queue. Given that there are x packets in the queue and the number of packets in the queue increases by v , the number of dropped packets is $v - (X - x)$ for $v > X - x$, and zero otherwise. The average number of dropped packets per time slot is obtained as follows:

$$\bar{x}_{drop} = \sum_{j=1}^P \sum_{z=X-x+1}^A [\vec{\pi}]_j (z - (X - x)) \times \left(\sum_{k=1}^{S2^I} [\mathbf{p}_{\lfloor j/(S2^I) \rfloor, \lfloor j/(S2^I) \rfloor + z}]_{j - \lfloor j/(S2^I) \rfloor S2^I, k} \right)$$

where $P = (X + 1)S2^I$ and $S2^I$ denote the size of matrix $\mathbf{P}$ and $\mathbf{p}_{x,x'}$, respectively. X is the maximum queue size. $[\vec{\pi}]_j$ denotes the element at row j of a vector $\vec{\pi}$.

$[\mathbf{p}_{\lfloor j/(S2^I) \rfloor, \lfloor j/(S2^I) \rfloor + z}]_{j - \lfloor j/(S2^I) \rfloor S2^I, k}$ denotes the element at row $j - \lfloor j/(S2^I) \rfloor S2^I$ and column k of matrix $\mathbf{p}_{\lfloor j/(S2^I) \rfloor, \lfloor j/(S2^I) \rfloor + z}$. The lower and upper bounds of average number of dropped packets can be obtained in the same way as the average queue length by using the stationary probability vectors solved from (3.15).

After calculating the average number of dropped packets per time slot, we can obtain the probability

that an incoming packet is dropped as follows:

$$P_{drop} = \frac{\bar{x}_{drop}}{\bar{\lambda}} \quad (3.34)$$

where $\bar{\lambda}$ is the average packet arrival rate obtained from (3.16).

Queue Throughput

Queue throughput measures the average number of packets transmitted in one time slot. This is calculated based on the fact that if an arriving packet is neither blocked nor dropped upon its arrival, it will be transmitted eventually. Hence, the queue throughput (packets/time slot) can be obtained from

$$\eta = \bar{\lambda}(1 - P_{drop}). \quad (3.35)$$

The lower and upper bounds of queue throughput are obtained given the upper and lower bounds of packet dropping probability, respectively.

Average Delay

Average delay is defined as the number of time slots that a packet waits in the queue since its arrival until it is transmitted. We use Little's law to obtain the average delay as follows:

$$\bar{d} = \frac{\bar{x}}{\eta} \quad (3.36)$$

where η is the throughput (the same as the effective arrival rate at the queue) and $\bar{x}$ is the average number of packets in the queue. The lower bound of average delay is obtained given the lower bound of mean number of packets in queue and the upper bound of queue throughput. In contrast, the upper bound of average delay is obtained given the upper bound of mean number of packets in queue and the lower bound of queue throughput.

3.5.2 Parameter Setting

The number of mini-slots per time slot is $M = 10$. The number of interfaces is $F \in \{1, 2\}$, and the number of available channels (i.e., the number of primary users) is $I = 2$. The nominal value of the probability matrices of channels 1 and 2 are $\mathbf{C}_1 = \begin{bmatrix} 0.6 & 0.4 \\ 0.6 & 0.4 \end{bmatrix}$, and $\mathbf{C}_2 = \begin{bmatrix} 0.55 & 0.45 \\ 0.55 & 0.45 \end{bmatrix}$, respectively. The channel quality of each channel is $\bar{\gamma}_i = 10\text{dB}$. The number of secondary users is $S = 2$, and the queue size of each user is $X = 12$ packets. For the transmission of the secondary controller, $R = 4$ transmission modes are available. In each mode, binary phase shift keying, quadrature phase shift keying, and 16 quadrature amplitude modulation schemes with coding rate 1/2 and 3/4 are used. Each transmission mode can achieve a spectral efficiency from 0.5, 1.0, 1.5, and 2.0 bits/Hz where SNR threshold Γ_r for each mode is 6.4, 9.4, 11.2, and 16.4dB.

We assume a Poisson traffic arrival process for the packets to be transmitted to a secondary user. With mean rate λ , the probability that a packets arrives in time slot with length Δt is given by $\mathbf{A}_a = f_a(\lambda) = \frac{e^{-\lambda\Delta t}(\lambda\Delta t)^a}{a!}$, for $a \in \{0, 1, \dots, A\}$. In this case, A is the maximum batch size for packet arrival and $\mathbf{A}_A = f_A(\lambda) = \sum_{a=A}^{\infty} f_a(\lambda)$. The packet arrival rate λ is one packet per time slot. The uncertainty range is set to ± 0.05 which is the distance from channel state transition probability's nominal value to its lower bound value or upper bound value.

3.5.3 Numerical Results

Queue Distribution

Fig. 3.2 shows the queue distribution of a secondary user. The upper and lower bounds of the probability of a queue with certain number of packets are shown. Note that because the upper and lower bounds of queue distribution are obtained for a particular state (i.e., queue length and channel states), the total probabilities of lower or upper bound at all states do not need to be one which is the result of optimal solution obtained by solving the problem defined in (3.15).

Impact of Queue Size

Figs. 3.3(a), (b), and (c) show the packet dropping probability, queue throughput, and delay under varied queue size. The lower bound, upper bound, and nominal value of the channel state transi-

Figure 3.2: Queue distribution of a secondary user.

tion matrix are considered. As the queue size increases, the packet dropping probability decreases because more packets can be stored in a queue, which reduces the chance of the queue to be full. Because more packets can be stored in the queue, the queue throughput increases as the queue size increases. However, because there are more packets waiting in the queue, the delay increases. We observe that all performance measures obtained from the nominal value are always between the lower and upper bounds. In addition, when the queue size grows, the upper bound of packet dropping probability and the nominal value approach the lower bound. This is because if the queue size approaches infinity, then the uncertainty in the channel state transition probability only causes a fluctuation in the waiting length of the queue (i.e., average queue length in an infinity queue size scenario). Although here the queue size is not equal to infinity, as it grows, it becomes more and more large enough to tolerate the fluctuation of average queue length. As a result, the packet dropping probability approaches 0. From (3.35), as the queue size increases, the throughput gradually becomes less affected by the packet dropping probability and only related with the average packet arrival rate which is constant in the scenario discussed here. Hence, the upper bound of queue throughput and the nominal value approach the lower bound when queue size grows. However, because the fluctuation of average queue length is not too much affected by the increasing queue size, from (3.36), we can understand why the upper bound of average delay and the nominal value do not approach the lower bound when queue size grows.

The results obtained here can be also used to design the system. Given the performance requirements (e.g., maximum acceptable packet dropping probability or minimum acceptable queue throughput), the system parameters (i.e., minimum queue size and maximum packet arrival rate) of a secondary user can be determined. From the analysis with uncertainty, we can consider three choices of design parameters, i.e., conservative, progressive, and moderate. For the conservative and progressive

Figure 3.3: Impact of queue size on (a) packet dropping probability, (b) queue throughput, and (c) average delay.

choices, the worst-case and best-case performances are considered, respectively. For moderate choice, the nominal performance is considered. Fig. 3.4(a) shows the minimum queue size of a secondary user, enabling the packet dropping probability to be maintained at the threshold. As expected, as the threshold of packet dropping probability increases (i.e., performance requirement becomes less strict), the minimum queue size can be reduced, which results in a smaller required memory size. On the other hand, as the threshold of queue throughput increases (i.e., performance requirement becomes stricter), the minimum queue size has to be expanded to avoid the probability of queue to overflow (Fig. 3.4(b)). In both Figs. 3.4(a) and (b), the conservative choice yields the largest queue size because the worst-case performances are considered. On the other hand, the progressive choice yields the smallest queue size because the best case performance is considered.

Impact of Packet Arrival Rate

The packet arrival rate is varied. Figs. 3.5(a), (b), and (c) show respectively the packet dropping probability, queue throughput, and delay for the lower bound, the upper bound, and the nominal value. As the packet arrival rate increases, the queue becomes full more easily, and hence more packets will be dropped, which leads to higher packet dropping probability. Also, because there are more packets arriving and waiting in the queue, the delay increases. However, as there are more incoming packets, the secondary controller can transmit more data, and hence, the throughput increases. To understand the trend of curves in the scenario discussed here, we consider an inverse direction. When the packet arrival rate becomes smaller (i.e., from four packets per time slot to one packet per time slot), the average queue length, no matter if its upper bound or lower bound, will

Figure 3.4: Choice of queue size for (a) packet dropping probability threshold and (b) queue throughput threshold.

decrease accordingly. Then, the constant queue size here will become more tolerant of the fluctuation in the average queue length that is caused by the uncertainty in the channel state transition probability. In this way, the packet dropping probability approaches 0. As analyzed in the previous subsection, the upper bound of packet dropping probability and the nominal value approach the lower bound when the packet arrival rate decreases. For the same reasons as that analyzed in previous subsection, when the packet arrival rate decreases, the upper bound of queue throughput and the nominal value approach the lower bound, and the upper bound of average delay and the nominal value do not approach the lower bound.

Figure 3.5: Impact of packet arrival rate on (a) packet dropping probability, (b) queue throughput, and (c) average delay.

Also, the maximum packet arrival rates given the threshold of packet dropping probability and the minimum packet arrival rate given the threshold of queue throughput are considered with conservative, progressive and moderate choices of design. Fig. 3.6(a) shows the maximum packet arrival rate such that the packet dropping probability is lower than or equal to the threshold. As the threshold of packet dropping probability increases (i.e., less strict performance requirement), the packet arrival rate can increase. Fig. 3.6(b) shows the minimum packet arrival rate for each specific threshold of queue throughput. As the threshold of queue throughput increases, the packet arrival rate will be increased to ensure that enough queue throughput can be achieved. As a result, the conservative choice yields the largest packet arrival rate because of worst-case performance consideration.

Figure 3.6: Choice of packet arrival rate for (a) packet dropping probability threshold and (b) queue throughput threshold.

Impact of Uncertainty Range

As the uncertainty range increases, the difference between the upper bound and lower bound of the channel available probability which can be derived from (3.1) will increase. Except the scenario with nominal values, we only consider the scenario where the two channels are in their upper bounds of available probabilities and the scenario where the two channels are in their lower bounds of available probabilities so as to obtain the upper bound and lower bound curves shown in Fig. 3.7. The curves that can be obtained from other neglected scenarios should be between the upper bound and lower bound curves. Hence, as the uncertainty range increases, the upper bounds of available probabilities of the two channels will increase. Then secondary users can have more chance to utilize the channels so that the lower bound of packet dropping probability will decrease, and the

Figure 3.7: Impact of uncertainty range on (a) packet dropping probability, (b) queue throughput, and (c) average delay.

upper bound of queue throughput will increase, and the lower bound of average delay will decrease. On the other hand, as the uncertainty range increases, the lower bounds of available probabilities of the two channels will decrease. Then, the trend of the upper bound of packet dropping probability, the lower bound of queue throughput, and the upper bound of average delay can be explained in an inverse way. In this case, because the nominal value of each stationary probability does not change, the corresponding performance measures remain the same regardless of the changing of uncertainty range. Here the packet arrival rate is set to six packets per time slot.

3.6 Conclusion

In this chapter, we have studied the D-norm uncertainty and its impact on the performance measures in a cognitive radio network. The cognitive radio network is composed of a secondary controller and several secondary users in which the secondary controller is capable of opportunistically accessing channels of primary users and managing packet transmission to each secondary user. Using the approach of Markov chain with uncertainty, we have analyzed the lower and upper bounds performances (i.e., mean number of packets in queue, packet dropping probability, queue throughput, and average delay) of a secondary user. These lower and upper bounds can be used to investigate the cognitive radio network in the worst-case and best-case scenarios, which will be useful for the design of radio resource management for secondary users.

Chapter 4

Deferrable Load Scheduling under Imperfect Data Communication Channel

4.1 Introduction

In traditional power systems, the information regarding the system status (e.g., power consumption amount of each consumer, operating status of power transmission lines or distribution stations) are measured and recorded by analog devices. Usually the information is periodically retrieved by the system operator (e.g., power production company and public utility) in a manual way (e.g., sending personnel to collect the data and report to the headquarters). On the other hand, the information of interest to consumers, for example, the power price, is also disseminated by the system operator in a manual way (e.g., by sending mails or using public media to inform consumers). However, unlike the traditional power systems, in the next generation power system, the smart grid, the information transmission of both upstream (i.e., from consumers to the system operator) and downstream (i.e., from the system operator to consumers) becomes much faster and more convenient, because various kinds of computer networks are embedded in the smart grid with the aid of advanced data communication technologies to facilitate information flow. These computer networks are hierarchically organized under the framework called advanced metering infrastructure (AMI) [114].

AMI in smart grid provides an intelligent, bidirectional connection between consumers and the

system operator [115]. The networks in AMI can be categorized in terms of coverage area into three types: HAN, NAN, and WAN [116]. As shown in Fig. 4.1, in a residential house, through HAN, the smart meter can gather the data measured by sensors implanted in home appliance and control the operation of appliance (i.e., turn on/off) through actuators embedded in them. The data gathered by the smart meter are sent forward to a DAU through NAN. A NAN can cover several residential houses or a community and a DAU acts as the gateway of the NAN. Through WAN, the meter data are relayed by DAU to the MDMS where the data will be used for decision making with an objective of minimizing the power supply and power consumption costs. On the other hand, for the downstream, the information from the MDMS (e.g., power price or regulation orders) is transmitted through these networks downwards to the smart meter. The smart meter uses the information to perform residential energy-consumption scheduling [117] or just executes the commands from the MDMS to handle emergency events (e.g., power outage). In a word, the power system in smart grid is responsible for energy flow, while AMI is responsible for information flow. These two sub-systems of smart grid work cooperatively so as to achieve a better performance than that of the traditional power system.

Figure 4.1: System model for deferrable load scheduling.

The problem studied in this chapter, deferrable load scheduling, belongs to an important issue in smart grid, demand-side management. Demand-side management arises as an important issue because a more stable power demand profile will enable the available generating capacity to be used more efficiently, save the cost for installing new generation and transmission infrastructure, and reduce the regulation cost of the system operator. Hence, to reduce power demand during peak hours, the RTP [118, 119] is implemented by the public utility. The term “public utility” refers

to as a company or organization which provides power services to the public. The public utility buys power from power plants and sells it to consumers. The public utility is also responsible for the deployment and maintenance of the infrastructure used for power transmission and distribution. When RTP is adopted by the public utility, the power price is dynamically decided by the MDMS based on the power demand and the power production on the power consumer's and supplier's sides, respectively. A lower power price is offered as an incentive to attract consumers to run as much load as possible in off-peak hours. On the other hand, a higher power price during peak hours is used to limit unnecessary power consumption when the expected power demand is larger than the estimated power supply. As a result, a more steady power demand profile can be achieved, which is also beneficial to the public utility.

The power consumption behavior will become more adaptive to RTP, if the deferrable load can be scheduled more wisely. The deferrable load (e.g., washer/dryer, air conditioner [120]) is a kind of power consumption units whose operation can be postponed. The scheduler embedded in the smart meter can be used to defer the load's operation when the power price is high and to allow the load to consume power later when the price becomes cheap [117]. The decision made by the scheduler is based on the real-time power price. The minimum power consumption cost can be achieved if the power price is always available to the scheduler. Without price information or with incomplete power price information, the optimal decision of the deferrable load scheduling cannot be made. Therefore, the availability of AMI is important for the scheduler to make an optimal decision. In the literature, the interdependency between communication network and power system in smart grid has been analyzed [121]. Besides, some methods for improving the reliability of wireless networks used in smart grid have been studied [122]. However, few work quantitatively assesses the impact of network reliability on the power consumption cost or provides some feasible methods to mitigate the impact.

In this chapter, we consider the deferrable load scheduling under different data communication availability conditions to transfer power price information. In order to assess the impact of network reliability on the system, specifically on the power consumption cost and to provide feasible methods to alleviate the negative impact, the following work has been done in our research.

- The optimal deferrable load scheduling policy is obtained with complete power price information (i.e., power price is always observable to the scheduler). This corresponds to the case that the data communication between MDMS and the smart meter is always available. The MDP model is formulated and solved to obtain the optimal policy.

- The deferrable load scheduling policy is obtained with incomplete power price information (i.e., power price may not be always available to the scheduler). This corresponds to the situation that the data connection can be unavailable occasionally due to interference, congestion, malfunction of network devices or even cyber attacks. Two approaches to obtain the scheduling policy in this situation are as follows:
 - When the power price information is not available, the scheduler can use historical price information to make the decision. The MDP is applied to obtain the scheduling policy.
 - The power price information is assumed to be partially observable. The POMDP method is applied to obtain the deferrable load scheduling policy with incomplete information.

In summary, we present the optimization framework, which can be used not only to obtain the deferrable load scheduling policy and assess the impact of communication network's unavailability on the power consumption cost, but also to determine the channel selection strategy. Note that though in this chapter, we mainly focus on studying the impact of data communication availability based on NAN, the analysis can be straightforwardly extended to the WAN and the multi-hop connection between the consumer's side and the MDMS.

The rest of this chapter is organized as follows. Section 4.2 gives the system model. In Section 4.3, the deferrable load scheduling problem with perfect data connection is discussed and solved. In Section 4.4, the deferrable load scheduling problem with imperfect data connection without and with the standby channel is solved through the MDP method and the average price is used when the data connection is not available. In Section 4.5, the POMDP is formulated to solve the scheduling problem with imperfect data connection without and with the standby channel and a belief vector is utilized to estimate the actual price level. The performance evaluation of different scheduling approaches is presented in Section 4.6. The conclusion of the chapter is given in Section 4.7.

4.2 System Model

4.2.1 Deferrable Load Scheduling and Real-Time Pricing

We consider a deferrable load whose operations can be scheduled based on real-time power price information provided by the public utility. The operation of a deferrable load is divided into h_m stages. The deferrable load has less time constraint, in which its operation in each stage can

be delayed (e.g., until the power price is low). To minimize the power consumption, a scheduler embedded in the smart meter can be used to optimize the operation of the deferrable load in each stage. We assume that the scheduler operates on a time slot basis, where each stage of the deferrable load's operation corresponds to one time slot. In each stage, the scheduler can choose to run or delay the deferrable load. If the scheduler decides to run, the deferrable load consumes power and the power cost will be paid by the consumer according to the power price. The load¹ may consume different amounts of power at different stages. On the other hand, if the load is deferred, the power consumption is assumed to be zero. The maximum number of time slots that the load can be deferred in each stage is bounded by the deferment limit d_m . For example, for $d_m = 2$, the load can be deferred for 2 time slots at most. When the load has been deferred for d_m time slots, it is mandatory to run the load in the next time slot. Once the load runs all h_m stages, a job is finished. The scheduler can maintain a queue to buffer arriving jobs. The maximum queue size is assumed to be l_m .

Figure 4.2: State transition of power price.

RTP is adopted by the public utility, where the power price information is sent by the public utility periodically in each time slot. We assume that the power price is divided into different levels from low to high. The Markov chain can then be used to model the power price adaptation. For example, if there are three price levels (i.e., low, moderate, and high), the price transition is modeled as a three-state Markov chain whose state transition diagram is shown in Fig. 4.2. Note that the similar assumption is made in other works (e.g., [123]).

¹For the rest of this chapter, “deferrable load” and “load” are used interchangeably.

4.2.2 Smart Grid Data Communication Infrastructure

We consider the data communication infrastructure to support various smart grid applications, including deferrable load scheduling as shown in Fig. 4.1. A smart meter is connected with a NAN through a DAU. The smart meter receives real-time power price information and then forwards to the scheduler which will make a decision on power consumption. In the system model under consideration, we assume that a cognitive radio network is used for the NAN to reduce the cost paid for data transmission. The smart meter plays the role of a secondary user in the cognitive radio network and performs DSA [124] to opportunistically use the licensed channel which belongs to a primary user. In a cognitive radio network, the primary user has the privilege of using its licensed channel at any time it wants. The smart meter can only access the licensed channel in some time slots when it is temporarily not occupied by the primary user [125]. Therefore, the licensed channel, also called the default channel in our context, may not be always available to the smart meter. Besides, the NAN may suffer from interference, hardware malfunction, software failures, or cyber attacks such as denial-of-service. The data connection between the smart meter and NAN used to transfer power price information for the deferrable load scheduling may not be always available. When the data connection is not available, the smart meter cannot receive the power price information. Lacking of the power price information, the scheduler cannot make an optimal decision. To solve such a problem, a standby alternative channel (e.g., 3G cellular network) can be used to receive the power price information. It is assumed that the standby channel is always available, but accessing it will incur additional cost.

To analyze the impact of data communication unavailability on the deferrable load scheduling problem, we consider three cases, i.e., perfect default channel, imperfect default channel, and imperfect default channel with the POMDP based algorithm.

Case 1: Perfect Default Channel

The default channel between a smart meter and NAN is assumed to be always available. The scheduler can receive the power price information at the beginning of every time slot. Since the power price information is complete, the optimal scheduling policy can be obtained. Therefore, in this case, the cost paid for power consumption will be the lowest. In Section 4.3, the MDP is formulated for the deferrable load scheduling problem, and the value iteration algorithm is used to obtain the optimal policy. Because the default channel is assumed to be perfect, the smart meter

does not need to access the standby channel and pay the access price.

Case 2: Imperfect Default Channel

However, in practice, the default channel may not be always available. Therefore, we consider the case in which the default channel is unavailable randomly and the smart meter can be disconnected from the NAN in some time slots. If the data communication is not available, the real-time price information cannot be received by the smart meter. In this case, the scheduler will use the average price to make a decision for the deferrable load. The unavailability of the power price information will result in a suboptimal scheduling decision and extra cost to the consumer. More details about the average price and standby channel access in this case will be given in Section 4.4.

With an imperfect default channel, we assume that the default channel is modeled as a two-state “on-off” Markov chain with parameters (α, β) , where α is the transition probability from the “unavailable” (i.e., “off”) state to “available” (i.e., “on”) state and β is the transition probability from the “available” state to “available” state. The state transition matrix of the channel model can be expressed as follows:

$$\mathbf{C} = \begin{bmatrix} 1 - \alpha & \alpha \\ 1 - \beta & \beta \end{bmatrix}, \quad (4.1)$$

where the first and the second rows correspond to the states “unavailable”, and “available”, respectively.

Again, the MDP is formulated for the deferrable load scheduling problem. Moreover, the standby channel access is jointly optimized based on the access price. Expectedly, the cost of the deferrable load scheduling in this case will be higher than that in the case of perfect default channel.

Case 3: Imperfect Default Channel with the POMDP-Based Scheduling Algorithm

An imperfect default channel is considered. However, the scheduler implements the POMDP-based algorithm to obtain the scheduling policy, in which the power price information is partially observable. The time slot structure of this case is shown in Fig. 4.3. At the beginning of each time slot, the scheduler will try to obtain the power price information by accessing either the default channel or the standby channel. The scheduler can observe the power price information when the data connection is available. Otherwise, the scheduler cannot observe the price information. According to the

Figure 4.3: Time slot structure for deferrable load scheduling with POMDP-based algorithm.

observation, the scheduler's belief about the power price level is updated. Then, unlike Case 2, the load scheduling decision in this Case 3 is made based on the scheduler's belief of the power price level in the current time slot. In Section 4.5, the POMDP is formulated, and both the scheduling policy and channel accessing policy can be jointly optimized. From the performance evaluation presented in Section 4.6, it is shown that the POMDP-based scheduling algorithm can achieve the cost lower than that in Case 2, but higher than that in Case 1.

4.3 Case 1: Perfect Default Channel

In this section, we assume the smart meter can always receive the actual power price information. We model the deferrable load scheduling problem as an MDP model defined as $\langle \mathcal{S}, \mathcal{A}, Q, \mathcal{F} \rangle$, where $\mathcal{S}$ is the state space, $\mathcal{A}$ is the action space, Q is the transition probability matrix, and $\mathcal{F}$ is the immediate cost function defined for each state when different actions are taken.

The state space $\mathcal{S}$ is defined as follows:

$$\mathcal{S} = \left\{ (l, d, g, h); l = \{0, 1, \dots, l_m\}, d = \{0, 1, \dots, d_m\}, g = \{0, 1, \dots, g_m\}, h = \{0, 1, \dots, h_m\} \right\} \quad (4.2)$$

where l represents the number of deferrable jobs including the running job currently served by the scheduler and l_m is the maximum queue size. d represents the wait state (i.e., the number of time slots that the running job has already been deferred), and d_m is the deferment limit (i.e., maximum number of time slots that the job can be deferred in each stage). g represents the price level, and g_m represents the highest price level. h represents the current stage of the running job. 0 and h_m are the first and final stages, respectively.

The action space is defined as $\mathcal{A} = \{a_1, a_2\}$, where a_1 is the action to run the load and consume

power at stage h in the current time slot. a_2 is the action to defer the load. First, the transition probabilities are derived for actions a_1 and a_2 , respectively.

4.3.1 Transition Probability Matrix for Action “Run”

Let $\mathbf{S}^u(run)$ and $\mathbf{S}^f(run)$ denote the probability matrices for the transition of stage h and wait state d when no job is being finished and the job is being finished at the end of the current time slot, respectively, given the current action is “run”. The rows of these matrices correspond to states $(0, 0), \dots, (0, d), \dots, (0, d_m), \dots, (h, d), \dots, (h_m, 0), \dots, (h_m, d_m)$. The elements of these matrices can be obtained as follows:

$$S_{(h,d),(h',d')}^u(run) = \begin{cases} 1 & h \neq h_m, h' = h + 1, d' = 0, \\ 0, & \text{otherwise,} \end{cases} \quad (4.3)$$

$$S_{(h,d),(h',d')}^f(run) = \begin{cases} 1 & h = h_m, h' = 0, d' = 0, \\ 0, & \text{otherwise,} \end{cases} \quad (4.4)$$

where $S_{(h,d),(h',d')}^u(run)$ and $S_{(h,d),(h',d')}^f(run)$ are the transition probabilities from state (h, d) to state (h', d') in matrices $\mathbf{S}^u(run)$ and $\mathbf{S}^f(run)$, respectively. The probability defined in (4.3) corresponds to the transition to the next stage and the wait state is reset to 0. The probability in (4.4) corresponds to that when all stages are finished, the current running job is finished. Then the next job waiting in the queue is now served, and the stage and the wait state are reset to the initial value $(0, 0)$.

Let $\mathbf{P}$ denote the price level transition probability matrix [123] (as shown in Fig. 4.2). Then, we can combine the transition of the stage, wait state and price level. $\mathbf{T}^u(run)$ and $\mathbf{T}^f(run)$ express the transition matrices of the composite states. $\mathbf{T}^u(run)$ and $\mathbf{T}^f(run)$ can be obtained as follows:

$$\mathbf{T}^u(run) = \mathbf{P} \otimes \mathbf{S}^u(run), \quad \mathbf{T}^f(run) = \mathbf{P} \otimes \mathbf{S}^f(run), \quad (4.5)$$

where $\otimes$ is the Kronecker product.

Next, the queue state transition is combined, and the resulting transition probability matrix for all

state transitions under state space $\mathcal{S}$ with action “run” is given by:

$$\mathbf{Q}(run) = \begin{bmatrix} \mathbf{Q}_{0,0} & \mathbf{Q}_{0,1} & & & \\ \mathbf{Q}_{1,0} & \mathbf{Q}_{1,1} & \mathbf{Q}_{1,2} & & \\ & \ddots & \ddots & \ddots & \\ & & & \mathbf{Q}_{l_m,l_m-1} & \mathbf{Q}_{l_m,l_m} \end{bmatrix} \quad (4.6)$$

where $\mathbf{Q}_{l,l'}$ is the transition probability matrix when the current number of jobs in the queue is l and becomes l' . These matrices can be obtained as follows:

$$\mathbf{Q}_{0,0} = \mathbf{P} \otimes \begin{bmatrix} (1-\lambda) & 0 & \cdots & 0 \\ \vdots & \vdots & & \vdots \\ (1-\lambda) & 0 & \cdots & 0 \end{bmatrix}, \quad \mathbf{Q}_{0,1} = \mathbf{P} \otimes \begin{bmatrix} \lambda & 0 & \cdots & 0 \\ \vdots & \vdots & & \vdots \\ \lambda & 0 & \cdots & 0 \end{bmatrix}, \quad (4.7)$$

$$\mathbf{Q}_{l,l-1} = (1-\lambda)\mathbf{T}^f(run), \quad (4.8)$$

$$\mathbf{Q}_{l,l} = (1-\lambda)\mathbf{T}^u(run) + \lambda\mathbf{T}^f(run), \quad (4.9)$$

$$\mathbf{Q}_{l,l+1} = \lambda\mathbf{T}^u(run), \quad (4.10)$$

$$\mathbf{Q}_{l_m,l_m} = (1-\lambda)\mathbf{T}^u(run) + \lambda\mathbf{T}^f(run) + \lambda\mathbf{T}^u(run), \quad (4.11)$$

where λ is the new job arrival probability. In (4.7), the transition matrices $\mathbf{Q}_{0,0}$ and $\mathbf{Q}_{0,1}$ are defined from the fact that if there is no job in the queue, the initial values of both stage and wait states must all be 0. $\mathbf{Q}_{l,l-1}$, $\mathbf{Q}_{l,l+1}$, and $\mathbf{Q}_{l,l}$ are for the cases that the number of jobs in the queue decreases, increases, and does not change, respectively. For $\mathbf{Q}_{l,l-1}$, the number of job decreases when the job is finished at the final stage and there is no new arriving job. For $\mathbf{Q}_{l,l+1}$, the number of jobs increases when the job is run at the intermediate stage and there is a new arriving job. For $\mathbf{Q}_{l,l}$, the number of jobs does not change when the job is run at the intermediate stage and there is no new arriving job, or when the job is finished at the final stage and there is a new arriving job. For $\mathbf{Q}_{l_m,l_m}$, the queue is full when a new job arrives and the current job is still at the intermediate stage. As a result, the new job will not be admitted into the queue.

4.3.2 Transition Probability Matrix for Action “Defer”

For the action “defer”, similarly we use $\mathbf{S}^u(defer)$ and $\mathbf{S}^f(defer)$ to denote the probability matrices for the transition of stage h and wait state d , when no job is finished or the job is finished at the

end of the current time slot, respectively. The elements of matrices $\mathbf{S}^u(defer)$ and $\mathbf{S}^f(defer)$ are obtained as follows:

$$S_{(h,d),(h',d')}^u(defer) = \begin{cases} 1, & (h \neq h_m, d = d_m, h' = h + 1, d' = 0) \text{ OR} \\ & (h \neq h_m, d \neq d_m, h' = h, d' = d + 1) \text{ OR} \\ & (h = h_m, d \neq d_m, h' = h_m, d' = d + 1), \\ 0, & \text{otherwise,} \end{cases} \quad (4.12)$$

$$S_{(h,d),(h',d')}^f(defer) = \begin{cases} 1 & h = h_m, d = d_m, h' = 0, d' = 0, \\ 0, & \text{otherwise.} \end{cases} \quad (4.13)$$

The probability defined in (4.12) corresponds to the case that the current job will not be accomplished if it is not at the final stage or if it is at the final stage, but it is not at the final wait state d_m . The probability defined in (4.13) corresponds to the case that if the current job is at the final stage and the final wait state is reached, then it is mandatory to run the job and accomplish it.

Following the same procedure for the action “run”, we can obtain $\mathbf{Q}(defer)$ that is the transition probability matrix for all state transitions under space $\mathcal{S}$ when action “defer” is taken.

4.3.3 Optimization Formulation

We assume that the time horizon of the deferrable load scheduling is finite (e.g., to run the load within a day), we apply the value iteration algorithm to find the optimal policy [126]. The immediate costs are defined as follows:

$$F_{(l,d,g,h)}^{a_1} = \begin{cases} F_g \gamma_h, & l \neq 0, l \neq l_m, \\ F_g \gamma_h + \lambda F_{drop}, & l = l_m, h \neq h_m, \\ F_g \gamma_h, & l = l_m, h = h_m, \\ 0, & l = 0 \end{cases} \quad (4.14)$$

$$F_{(l,d,g,h)}^{a_2} = \begin{cases} F_{def}, & l \neq 0, l \neq l_m, d \neq d_m, \\ F_{def} + \lambda F_{drop}, & l = l_m, d \neq d_m, \\ 0, & l = 0. \end{cases} \quad (4.15)$$

Recall that a_1 and a_2 are the “run” and “defer” actions, respectively. F_g is the power price at price level g and γ_h is the amount of power consumed by the load at stage h . F_{def} is the penalty cost for the “defer” action. F_{drop} is the cost if the arriving job cannot be admitted into the queue. Because the objective of the scheduling optimization is not only to minimize the cost paid for power consumption, but also to finish the job as soon as possible, F_{def} and F_{drop} are used to balance the two objectives. The second condition in (4.14) corresponds to the case that if the queue is full and the current running job is not yet at the final stage, then even though the load is run in the current time slot, there is a probability of λ that the arriving job will not be admitted into the queue. The third condition in (4.14) corresponds to the case that if the current running job is at its final stage, then the job will be finished in the current time slot. As a result, the arriving job will be admitted into the queue. The second condition in (4.15) corresponds to the case that if the queue is full and the action “defer” is taken, the probability that the arriving job will not be admitted into the queue is λ .

To be succinct, the immediate cost $F_{(l,d,g,h)}^a$ is expressed as F_i^a , where $i \in \mathcal{S}$. Applying the value iteration algorithm, we can iteratively find the optimal actions as follows:

$$\mathcal{V}_i^*(t) = \min_{a \in \mathcal{A}} F_i^a + \sum_{j \in \mathcal{S}} q_{i,j}^a \mathcal{V}_j^*(t+1), \quad \forall i \in \mathcal{S}, \quad (4.16)$$

where $q_{i,j}^a$ represents the transition probability in matrix $\mathbf{Q}(a)$, i is the state of the load in the current time slot and j is the state in the next time slot. Through (4.16), we can find the optimal action for each state at decision epoch t as follows:

$$a_i^*(t) = \arg \min_{a \in \mathcal{A}} F_i^a + \sum_{j \in \mathcal{S}} q_{i,j}^a \mathcal{V}_j^*(t+1), \quad \forall i \in \mathcal{S}. \quad (4.17)$$

Let T denote the length of the finite time horizon. Finally, we can find the optimal policy $\{a_i^*(1), a_i^*(2), \dots, a_i^*(T)\}$ and solve the deferrable load scheduling problem in the case of perfect default channel.

4.4 Case 2: Imperfect Default Channel

In this section, we study the deferrable load scheduling problem when the default channel between a smart meter and an NAN is not perfect. In particular, the default channel may be unavailable. To

improve the communication reliability, the smart meter can choose either the default channel or the standby channel to obtain power price information. To analyze the impact of channel selection, we first solve the deferrable load scheduling problem without the standby channel. Then we include the standby channel into our model, and solve the scheduling and channel selection problems jointly.

4.4.1 Without the Standby Channel

We formulate the scheduling problem in Case 2 without the standby channel as an MDP problem $\langle \mathcal{S}, \mathcal{A}, Q, \mathcal{F} \rangle$, where the meanings of $\mathcal{S}$, $\mathcal{A}$, Q , and $\mathcal{F}$ are the same as those in Case 1. However, the state space $\mathcal{S}$ is defined as follows:

$$\mathcal{S} = \left\{ (l, d, g, h, w); l = \{0, 1, \dots, l_m\}, d = \{0, 1, \dots, d_m\}, g = \{0, 1, \dots, g_m\}, \right. \\ \left. h = \{0, 1, \dots, h_m\}, w = \{0, 1\} \right\} \quad (4.18)$$

where l , d , g , and h have the same meanings as those in (4.2) of Section 4.3. In addition, w represents the state of the default channel that can be unavailable or available denoted by “0” and “1”, respectively.

Definition of the Transition Probability Matrix

Without the standby channel, the matrices $\mathbf{S}^u(a)$ and $\mathbf{S}^f(a)$ for the transition of stage h and wait state d are defined the same as those in Case 1, where a can be either “run” or “defer” action. Let $\mathbf{P}$ denote the price transition probability matrix. We can define the probability matrix for the transition of price level g and the default channel state w as follows:

$$\mathbf{J} = \begin{bmatrix} (1 - \alpha)\mathbf{I} & \alpha\mathbf{I} \\ (1 - \beta)\mathbf{P} & \beta\mathbf{P} \end{bmatrix}, \quad (4.19)$$

where $\mathbf{J}$ denotes the probability matrix for the transition of price level and default channel state. α and β are the transition probabilities of the default channel state as defined in (4.1). In the first row of matrix $\mathbf{J}$, the channel state in the current time slot is “unavailable”. As a result, the scheduler cannot observe the price level, and the identity matrix $\mathbf{I}$ with an appropriate size is applied (i.e., there is no change of price level from the scheduler’s perspective). In the second row of matrix $\mathbf{J}$, the channel state is “available”, and hence the scheduler can observe the price level. Therefore, the

matrix $\mathbf{P}$ is applied.

Then we can combine the transition of the stage, wait state, price level and default channel state by using $\mathbf{T}^u(a)$ and $\mathbf{T}^f(a)$ to denote the transition matrices of the composite four states, where a can be “run” or “defer” action. $\mathbf{T}^u(a)$ and $\mathbf{T}^f(a)$ can be obtained as follows:

$$\mathbf{T}^u(a) = \mathbf{J} \otimes \mathbf{S}^u(a), \quad \mathbf{T}^f(a) = \mathbf{J} \otimes \mathbf{S}^f(a), \quad (4.20)$$

where $\otimes$ is the Kronecker product.

To build the overall transition matrix $\mathbf{Q}$, the similar steps defined in (4.7), (4.8), (4.9), (4.10) and (4.11) are also applied. Note that matrix $\mathbf{P}$ in (4.7) should be substituted by matrix $\mathbf{J}$.

Optimization Formulation

Then the scheduling problem in Case 2 without the standby channel can be similarly formulated as in (4.16). The immediate cost function without the standby channel can be defined as follows:

$$F_{(l,d,g,h,w)}^{a_1} = \begin{cases} F_{ave}\gamma_h, & l \neq 0, l \neq l_m, w = 0, \\ F_{ave}\gamma_h + \lambda F_{drop}, & l = l_m, h \neq h_m, w = 0, \\ F_{ave}\gamma_h, & l = l_m, h = h_m, w = 0, \\ F_g\gamma_h, & l \neq 0, l \neq l_m, w = 1, \\ F_g\gamma_h + \lambda F_{drop}, & l = l_m, h \neq h_m, w = 1, \\ F_g\gamma_h, & l = l_m, h = h_m, w = 1, \\ 0, & l = 0, \end{cases} \quad (4.21)$$

$$F_{(l,d,g,h,w)}^{a_2} = \begin{cases} F_{def}, & l \neq 0, l \neq l_m, d \neq d_m, \\ F_{def} + \lambda F_{drop}, & l = l_m, d \neq d_m, \\ 0, & l = 0. \end{cases} \quad (4.22)$$

a_1 and a_2 denote the “run” and “defer” actions, respectively. The first condition in (4.21) corresponds to the case that when the default channel is unavailable (i.e., $w = 0$), the average price F_{ave} will be used as an alternative of the actual price. Let $\vec{\eta}$ denote the stationary probability vector of the price level g . $\vec{\eta}$ can be obtained by solving $\vec{\eta}^T \mathbf{P} = \vec{\eta}^T$ and $\vec{\eta}^T \vec{\mathbf{1}} = 1$, where $\vec{\mathbf{1}}$ is a vector of ones with an appropriate size. The average power price can be obtained from $F_{ave} = \vec{\eta}^T [F_0, \dots, F_{g_m}]^T$,

where F_0 and F_{g_m} are the power prices at the lowest and highest power levels, respectively. The fourth condition in (4.21) corresponds to the case that when the default channel is available (i.e., $w = 1$) the actual power price is used. The definitions of other conditions in (4.21) and (4.22) are similar to those in the case of perfect default channel.

Through the value iteration algorithm, the pseudo-optimal policy $\{a_i^*(1), a_i^*(2), \dots, a_i^*(T)\}$ in Case 2 without the standby channel can be obtained. The policy is called pseudo-optimal because the price information used in the scheduling process is incomplete and the immediate cost function F_i^a defined in (4.21) is inaccurate. Though the pseudo-optimal policy is applied by the scheduler, we should use the actual immediate cost function $\tilde{F}_i^a$ in which the average cost F_{ave} is substituted by the actual power price F_g to calculate the actual total cost paid by the customer. The transition probability matrix $\mathbf{Q}$ has to be modified as well. Specifically, the elements in the first row of matrix $\mathbf{J}$ should be modified as $(1 - \alpha)\mathbf{P}$ and $\alpha\mathbf{P}$. Because to calculate the actual total cost, we assume that the complete price information is available. Let $\tilde{\mathbf{Q}}$ denote the transition matrix after modification. Then using the value iteration function, the actual total cost can be calculated as follows:

$$\mathcal{V}_i^*(t) = \tilde{F}_i^{a^*} + \sum_{j \in \mathcal{S}} \tilde{q}_{i,j}^{a^*} \mathcal{V}_j^*(t+1), \quad \forall i \in \mathcal{S}, \quad (4.23)$$

where $\mathcal{V}_i^*(t)$ represents the actual total cost at state i in the t th time slot when the pseudo-optimal action a^* is taken and actual immediate cost function $\tilde{F}_i^a$ is applied. $\tilde{q}_{i,j}^{a^*}$ is the transition probability in the modified matrix $\tilde{\mathbf{Q}}$ when action a^* is taken.

4.4.2 With the Standby Channel

When the standby channel is available in the system, the scheduler can choose either the default channel or the standby channel to access. To access the channel optimally, the MDP formulation defined in Section 4.4.1 can be extended and solved for the optimal policy. In this case, the state space $\mathcal{S}$ of the extended MDP formulation is defined as follows:

$$\mathcal{S} = \left\{ (l, d, g, h, u, w); l = \{0, 1, \dots, l_m\}, d = \{0, 1, \dots, d_m\}, g = \{0, 1, \dots, g_m\}, \right. \\ \left. h = \{0, 1, \dots, h_m\}, u = \{0, 1\}, w = \{0, 1\} \right\} \quad (4.24)$$

where u is the indicator of the channel currently accessed. $u = 0$ and $u = 1$ represent that the default channel and standby channel are accessed, respectively. w represents the state of the default

channel in the current time slot. Because the standby channel is assumed to be always available, there is no need to keep track the state of the standby channel.

The action space $\mathcal{A}$ is extended as follows:

$$\mathcal{A} = A \cup B, \quad A = \{a_1, a_2\}, \quad B = \{b_0, b_1\}, \quad (4.25)$$

where a_1 and a_2 represent the actions to run and to defer the load in the current time slot, respectively. b_0 and b_1 represent the actions of accessing the default channel and accessing the standby channel in the next time slot, respectively.

Transition Probability Matrix

The matrices $\mathbf{S}^u(a_i, b_j)$ and $\mathbf{S}^f(a_i, b_j)$ for the transition of stage h and wait state d are defined the same as those in Case 2 without the standby channel, where a_i can be either “run” or “defer” action, and b_j can be any action in the action set B . Because the transition of stage h and wait state d does not depend on the channel access action, the transition matrices $\mathbf{S}^u(a_i, b_j)$ and $\mathbf{S}^f(a_i, b_j)$ are not affected by action b_j either. Here let $\mathbf{J}$ denote the probability matrix for the transition of the price level, the indicator of the channel currently accessed, and the default channel state. The elements of matrix $\mathbf{J}$ can be obtained as follows:

$$J_{(g,u,w)(g',u',w')}(a_i, b_j) = \begin{cases} P(g, g')C(w, w'), & j = u', (w = 1 \text{ OR } u = 1) \\ I_p(g, g')C(w, w'), & j = u', u = 0, w = 0, \\ 0, & \text{otherwise,} \end{cases} \quad (4.26)$$

where (g, u, w) and (g', u', w') represent the price level, the indicator of the channel currently accessed, and the default channel state in the current and the next time slots, respectively. $P(g, g')$ is the transition probability from the current price level g to the next price level g' . $I_p(g, g')$ is the element of an identity matrix with the same size as that of the price transition matrix $\mathbf{P}$. The first condition in (4.26) corresponds to the case that if action b_j is chosen, then j should be equal to the indicator of the channel accessed in the next time slot (i.e., u'). $w = 1$ indicates that the default channel is available. $u = 1$ indicates that the standby channel is accessed. In both of the two situations, the actual price level is observable and the probability in matrix $\mathbf{P}$ is applied. We assume that the state of the default channel is still observable to the scheduler even when the standby channel is accessed. For the second condition in (4.26), the state of the default channel currently accessed is

unavailable (i.e., $w = 0$). As a result, the actual price level is not observable. Then the probability in the identity matrix $\mathbf{I}_p$ is applied. That is, there is no change of price level from the scheduler's perspective.

Similarly, the transition matrices $\mathbf{T}^u(a_i, b_j)$ and $\mathbf{T}^f(a_i, b_j)$ can be obtained as in (4.20). The overall transition matrix $\mathbf{Q}$ for Case 2 with the standby channel can be obtained in the same way as defined in (4.7), (4.8), (4.9), (4.10) and (4.11).

Optimization Formulation

The scheduling problem in Case 2 with the standby channel can be similarly formulated as that defined in (4.16). Because the access price of the standby channel is not equal to 0, the immediate cost function is modified as follows:

$$F_{(l,d,g,h,u,w)}^{a_1,b_j} = \begin{cases} F_{ave}\gamma_h + F(b_j), & l \neq 0, l \neq l_m, u = 0, w = 0, \\ F_{ave}\gamma_h + \lambda F_{drop} + F(b_j), & l = l_m, h \neq h_m, u = 0, w = 0, \\ F_{ave}\gamma_h + F(b_j), & l = l_m, h = h_m, u = 0, w = 0, \\ F_g\gamma_h + F(b_j), & l \neq 0, l \neq l_m, (u = 1 \text{ OR } w = 1), \\ F_g\gamma_h + F(b_j) + \lambda F_{drop}, & l = l_m, h \neq h_m, (u = 1 \text{ OR } w = 1), \\ F_g\gamma_h + F(b_j), & l = l_m, h = h_m, (u = 1 \text{ OR } w = 1), \\ F(b_j), & l = 0, \end{cases} \quad (4.27)$$

$$F_{(l,d,g,h,u,w)}^{a_2,b_j} = \begin{cases} F_{def} + F(b_j), & l \neq 0, l \neq l_m, d \neq d_m, \\ F_{def} + \lambda F_{drop} + F(b_j), & l = l_m, d \neq d_m, \\ F(b_j), & l = 0. \end{cases} \quad (4.28)$$

If the default channel is accessed (i.e., $u = 0$), but its state is unavailable (i.e., $w = 0$), then the average power price F_{ave} is applied instead of the actual power price. If the default channel is available (i.e., $w = 1$), or if the standby channel is accessed (i.e., $u = 1$), then the actual price can be observed. As a result, the actual power price F_g is applied. $F(b_j)$ is the accessing cost incurred by the action b_j . If b_j is to access the default channel, the accessing cost is equal to 0. Otherwise, the accessing cost is larger than 0.

Again as in the previous subsection, the pseudo-optimal policy $\{(a_i^*(1), b_j^*(1)), (a_i^*(2), b_j^*(2)), \dots, (a_i^*(T), b_j^*(T))\}$ in Case 2 with the standby channel can be obtained.

- To calculate the actual total cost, the immediate cost function as defined in (4.27) is modified by replacing the average power price F_{ave} by the actual power price F_g as follows:

$$F_{(l,d,g,h,u,w)}^{a_1,b_j} = \begin{cases} F_g\gamma_h + F(b_j), & l \neq 0, l \neq l_m, u = 0, w = 0, \\ F_g\gamma_h + \lambda F_{drop} + F(b_j), & l = l_m, h \neq h_m, u = 0, w = 0, \\ F_g\gamma_h + F(b_j), & l = l_m, h = h_m, u = 0, w = 0, \\ F_g\gamma_h + F(b_j), & l \neq 0, l \neq l_m, (u = 1 \text{ OR } w = 1), \\ F_g\gamma_h + F(b_j) + \lambda F_{drop}, & l = l_m, h \neq h_m, (u = 1 \text{ OR } w = 1), \\ F_g\gamma_h + F(b_j), & l = l_m, h = h_m, (u = 1 \text{ OR } w = 1), \\ F(b_j), & l = 0. \end{cases} \quad (4.29)$$

- The transition matrix $\mathbf{Q}$ should also be modified by using the actual transition probabilities in $\mathbf{P}$ instead of the transition probabilities of the identity matrix (i.e., $\mathbf{I}_p$). That is, the elements of matrix $\mathbf{J}$ defined in (4.26) becomes

$$J_{(g,u,w)(g',u',w')}(a_i, b_j) = \begin{cases} P(g, g')C(w, w'), & j = u', \\ 0, & \text{otherwise.} \end{cases} \quad (4.30)$$

- The actual total cost in Case 2 with the standby channel can be obtained as in (4.23).

4.5 Case 3: Imperfect Default Channel with POMDP

The default channel is still not perfect. The difference between Case 2 and Case 3 is that in Case 3 the scheduler makes its decision on the operation of the deferrable load based on its belief of the price level. The belief is updated at each time slot according to the scheduler's observation. In this case, firstly we solve the scheduling problem using POMDP without the standby channel. Then the standby channel is incorporated in the optimization.

4.5.1 Without the Standby Channel

To solve the problem of incomplete power price information, the POMDP method is applied. The POMDP formulation for the deferrable load scheduling without the standby channel can be formu-

lated with $\langle \mathcal{S}, \mathcal{A}, \mathcal{Q}, \mathcal{O}, \mathcal{F} \rangle$. $\mathcal{S}$ is the system state space defined as follows:

$$\mathcal{S} = \left\{ (l, d, g, h, w); l = \{0, 1, \dots, l_m\}, d = \{0, 1, \dots, d_m\}, g = \{0, 1, \dots, g_m\}, \right. \\ \left. h = \{0, 1, \dots, h_m\}, w = \{0, 1\} \right\} \quad (4.31)$$

where l, d, g, h , and w represent the same states as those in (4.18) of Section 4.4.

$\mathcal{A}$ is the same action space as that in Case 2 without the standby channel. $\mathcal{Q}$ is the transition probability matrix. $\mathcal{O}$ is the observation model in POMDP. $\mathcal{F}$ is the immediate cost. We first provide the definition of the transition probability matrix $\mathcal{Q}$.

Definition of Transition Matrix

Again, the matrices $\mathbf{S}^u(a)$ and $\mathbf{S}^f(a)$ for the transition of stage h and wait state d are defined the same as those in Case 1, where a can be either “run” or “defer” action. Let $\mathbf{J}$ denote the probability matrix for the transition of the price level g and the default channel state w . The matrix $\mathbf{J}$ can be obtained as follows:

$$\mathbf{J} = \mathbf{C} \otimes \mathbf{P}. \quad (4.32)$$

By applying the POMDP method, a belief probability vector will be used to infer the actual state in the current time slot. The uncertainty of price level is modeled by the belief vector. Hence, different from (4.19), in (4.32), the transition probability $\mathbf{J}$ is obtained based on complete information. As a result, the price transition matrix $\mathbf{P}$ is always applied.

Then, following the same procedures performed in Case 2, the overall transition matrix $\mathbf{Q}(a)$ without the standby channel can be obtained.

Observation Model

One of the most important components in POMDP is the observation model. The reason is that in POMDP, the belief probability vector used to infer the actual state in each time slot is updated according to the observations. The observation model $\mathcal{O}$ includes the set of observation results and the observation probabilities. The set of observation results without the standby channel is defined as follows:

$$\theta = \{0, 1, \dots, g_m, \emptyset\}, \quad (4.33)$$

where θ denotes the observation regarding the price level. $\theta = g_m$ represents that the highest price level is observed. $\theta = \emptyset$ represents that the price level is not observable to the scheduler.

When action a is taken and the composite state transits to state j (i.e., $j \in \mathcal{S}$), the probability of observing θ can be obtained as follows:

$$O_{j,\theta}^a = \begin{cases} 1, & w = 1, \theta = g, \\ 1, & w = 0, \theta = \emptyset, \\ 0, & \text{otherwise,} \end{cases} \quad (4.34)$$

where g and w are sub-states in the composite state j . The first condition in (4.34) corresponds to the case that if the default channel is available, the price level in state j is observable. Otherwise, the price level cannot be observed.

Optimization Formulation

Based on POMDP, the deferrable load scheduling problem without the standby channel can be formulated as follows [127]:

$$V_t^*(\Omega) = \min_a \left[\sum_i \pi_i \left(F_i^a + \sum_{j,\theta} q_{i,j}^a O_{j,\theta}^a V_{t+1}^*(\Lambda(\Omega|a, \theta)) \right) \right], \quad i, j \in \mathcal{S}, \theta \in \Theta, \quad (4.35)$$

where i and j are the system states in the current and next time slots, respectively. θ is the observation obtained by the scheduler at the beginning of the $(t + 1)$ th time slot when action a is taken in the t th time slot. $\Omega = \{\pi_1, \pi_2, \dots, \pi_N\}$ is the belief probability vector, where $N = |\mathcal{S}|$. Each element π_i represents the belief probability that the system state is i in the current time slot. In (4.35), $V_t^*(\Omega)$ represents the optimal cost function of the current time slot. Because the actual state is unobservable, the belief probability π_i is used to weigh the cost function of each state in the current time slot. The cost function of each state in the current time slot consists of the immediate cost F_i^a and the optimal cost function of the next time slot. Because the uncertainty of the price level is modeled by the belief vector, the immediate cost F_i^a can be defined based on the complete information. This is the same as that in Case 1. Note that the sub-state w will not influence the definition of F_i^a .

$\Lambda(\Omega|a, \theta)$ is the update function for the belief probability vector. As we explained previously, because the scheduler cannot know the actual price level, the belief probability vector is used to

make the estimation. The update of the belief probability vector depends on the observation obtained by the scheduler. For a certain state $j \in \mathcal{S}$, applying the Bayes's rule, the update function $\Lambda(\Omega|a, \theta)$ can be given as follows:

$$\pi'_j = \frac{O_{j,\theta}^a \sum_n \pi_n q_{n,j}^a}{\sum_n \pi_n \sum_m q_{n,m}^a O_{m,\theta}^a}, \quad (4.36)$$

where π'_j is the belief probability of that the system is in state j in the next time slot. The optimal cost function $V_t^*(\Omega)$ is a function of the belief probability vector. The belief probability vector depends on the observations. As a result, in (4.35), the belief probabilities, the transition probability and the observation probabilities are used to weigh the optimal cost function in the next time slot (i.e., $V_{t+1}^*(\Lambda(\Omega|a, \theta))$). The purpose of the problem formulation in (4.35) is to solve for the optimal action, which can minimize the cost function $V_t^*(\Omega)$ of the t th time slot when the belief probability vector in the t th time slot is Ω . However, because the belief probability vector depends on the observations, the traditional value iteration algorithm cannot be used to solve the POMDP problem. Nevertheless, because the optimal cost function of each time slot is piecewise linear and convex [127], it can be written as the sum of several weighted vectors. Hence, the idea of value iteration can still be used. More detailed explanation for solving the POMDP problem can be found in [127]. We apply the algorithm proposed in [128] to solve the POMDP for deferrable load scheduling with the imperfect default channel.

4.5.2 With the Standby Channel

When the scheduler can choose either the default channel or the standby channel to access, the state space becomes

$$\mathcal{S} = \left\{ (l, d, g, h, u, w); l = \{0, 1, \dots, l_m\}, d = \{0, 1, \dots, d_m\}, g = \{0, 1, \dots, g_m\}, \right. \\ \left. h = \{0, 1, \dots, h_m\}, u = \{0, 1\}, w = \{0, 1\} \right\} \quad (4.37)$$

where l, d, g, h, u and w are the same states as those in (4.24) of Section 4.4.

The action space $\mathcal{A}$ should also be extended as follows:

$$\mathcal{A} = A \cup B, \quad A = \{a_1, a_2\}, \quad B = \{b_0, b_1\} \quad (4.38)$$

to include the actions of channel selection. The meanings of action sets A and B are the same as that in (4.25).

Definition of the Transition Matrix

The matrices $\mathbf{S}^u(a_i, b_j)$ and $\mathbf{S}^f(a_i, b_j)$ for the transition of stage h and wait state d are obtained the same as those in Section 4.4.2. Let $\mathbf{J}$ denote the probability matrix for the transition of the states g , u and w . The elements of matrix $\mathbf{J}$ can be obtained as follows:

$$J_{(g,u,w)(g',u',w')}(a_i, b_j) = \begin{cases} P(g, g')C(w, w'), & j = u', \\ 0, & \text{otherwise.} \end{cases} \quad (4.39)$$

The meaning of each condition in (4.39) is similar to that explained in the previous subsection and that in Section 4.4.2.

Then following the same procedures performed in the previous sections, the overall transition matrix $\mathbf{Q}(a_i, b_j)$ in Case 3 with the standby channel can be obtained, where $a_i \in A$ and $b_j \in B$.

Observation Model

The set of observation results is the same as that in the previous subsection. However, in Case 3 with the standby channel, the scheduler can always observe the price level if the standby channel is accessed. Hence, the definition of observation probability should be modified.

To avoid the conflict of notations, let a_ψ denote the “run” or “defer” action, and let b_μ denote the action of choosing the default channel ($\mu = 0$) or the standby channel ($\mu = 1$). When actions a_ψ and b_μ are taken, if the composite system state transits to state j , where $j \in \mathcal{S}$, the probability of observing θ can be obtained as follows:

$$O_{j,\theta}^{a_\psi, b_\mu} = \begin{cases} 1, & u = 1, \theta = g, \\ 1, & u = 0, ((w = 0, \theta = \emptyset) \text{ OR } (w = 1, \theta = g)), \\ 0, & \text{otherwise.} \end{cases} \quad (4.40)$$

The first condition in (4.40) corresponds to the case that if the standby channel is accessed, the price level is observable (i.e., $\theta = g$). The second condition in (4.40) corresponds to the case that if the default channel is accessed, the price level is only observable when the default channel is available.

Optimization Formulation

In Case 3 with the standby channel, the POMDP deferrable load scheduling can be formulated the same as in (4.35).

- The modified transition matrix $\mathbf{Q}$ and the observation probability $O_{j,\theta}^{a_\psi, b_\mu}$, which incorporate the standby channel as defined in (4.40), will be applied to obtain $V_t^*(\Omega)$ in (4.35).
- The immediate cost defined in (4.27) is modified by replacing the average power consumption cost F_{ave} with the actual power consumption cost F_g at price level g . This is because the uncertainty is modeled by the belief probability vector. Therefore, the immediate cost becomes the same as that in (4.29).
- The update function of the belief probability vector π_j' defined in (4.36) should use the modified transition probabilities and observation probabilities.

Then the POMDP based scheduling problem in Case 3 with the standby channel can be solved.

4.6 Performance Evaluation

4.6.1 Parameter Setting

In the simulation, we consider a deferrable load with 3 stages, which can be deferred for 2 time slots in each stage. The scheduler can have 4 jobs waiting in the queue. When the load is in operation, for simplicity, it is assumed that the load will consume the equal amount of power (e.g., $1kWh$) in all the stages. Here we consider three price levels: low, moderate, and high which have the prices of 2, 5 and 10 cents per kWh , respectively.

To balance the objectives of saving power consumption cost and running as many jobs as possible, the cost of each deferment is set to be 4.45. It is a penalty cost for the deferment action. The cost of dropping a job due to lack of space in a queue is set to be 0.75. The state transition probabilities of the default channel is set to be $\{\alpha = 0.5, \beta = 0.5\}$. As described in the system model in Section 4.2, the default channel is a licensed channel that is opportunistically accessed by the smart meter. The standby channel is assumed to be always available. The access prices of the default channel and the standby channel are set to be 0 and 0.35, respectively (i.e., the default channel is free to access).

4.6.2 Numerical Results

Figure 4.4: Average costs in three cases without standby channel and “always run” and “always defer” policies

Convergence of the Average Cost without the Standby Channel

The convergence of the average costs in Cases 1, 2, and 3 without the standby channel is shown in Fig. 4.4. From Fig. 4.4, we observe that the proposed POMDP based scheduling algorithm (i.e., Case 3) achieves a much better performance than that of the traditional scheduling algorithm used in Case 2. The average cost in Case 2 is the worst among three scheduling schemes. The reason is that the average price level will result in a severely suboptimal scheduling policy, incurring the highest cost. In Case 1, since the default channel is perfect, the average cost is the lowest among the three scheduling schemes.

In Case 3 of Fig. 4.4, the belief probability vector for inferring the actual price level is updated per time slot based on the observation obtained by the scheduler. The belief probability vector helps the scheduler to estimate the actual price level more accurately. As a result, this information helps to achieve the average cost close to that from Case 1, and hence in Case 3, a better performance can be obtained compared with that obtained in Case 2. Furthermore, the cases that the deferrable load “always runs” and “always defers” are also considered for comparison. The “always run” policy

Figure 4.5: Average costs in three cases without and with the standby channel

means that as long as the queue of jobs is not empty, the scheduler will run the load in every time slot. On the other hand, in the “always defer” policy, as long as the deferment limit is not reached, the scheduler will postpone the operation of the load in every time slot. From Fig. 4.4, we can observe that the average cost of the “always run” policy is higher than that obtained in Case 2 and that obtained for “always defer” policy. This is because that there is no scheduling in the “always run” strategy, the load is run even though the power price is still high. The average cost of the “always defer” policy is higher than that obtained in Case 2. This is due to the deferment penalty cost incurred from the “always defer” policy.

Impact of Standby Channel

We evaluate the benefit of having the standby channel for the scheduler. Without the standby channel, the average costs in Cases 2 and 3 shown in Fig. 4.5 are higher than those of their counterparts with the standby channel. The reason is that the availability of the default channel is lower than that of the standby channel. If there is no standby channel, the probability that the scheduler loses connection with the NAN will be much higher. Again, using only the average price level when there is no standby channel will deteriorate the average cost compared to that with the standby channel. Though the average price level is not used in Case 3, the low availability of the default channel will

Figure 4.6: Impact of job arrival probability on the average cost in three cases without and with the standby channel.

still degrade the scheduler's belief on the actual price level. Again, in Case 1, because the default channel is perfect, the average cost is the lowest.

Impact of Arrival Probability

We vary the values of some parameters and observe their impacts on the performances of different scheduling approaches. Firstly, let the job arrival probability λ increase from 0.6 to 1. Fig. 4.6 shows that as the job arrival probability increases, the average cost per time slot when the horizon length is 50 will increase. This is from the fact that as the job arrival probability increases, the load will be more occupied and the scheduler has to run more frequently. As a result, the power consumption cost will increase. Moreover, as the job arrival probability increases, the queue used for buffering the jobs has a higher chance to be full. As a result, the number of dropped jobs will increase, increasing the job dropping cost. Again, from Fig. 4.6, it is observed that if the scheduler can choose the standby channel to access (i.e., dashed lines in Fig. 4.6), the costs in Cases 2 and 3 will be lower than those of their counterparts without the standby channel (i.e., solid lines in Fig. 4.6). The average costs obtained for the “always defer” and “always run” policies are larger than those obtained for the other cases. Note that the average cost of the “always run” policy is the

Figure 4.7: Impact of deferment limit on the average cost in three cases without and with the standby channel.

highest and far higher than those of the other policies. Therefore, it is omitted from Fig. 4.6 for ease of presentation.

Impact of Deferment Limit

Let the deferment limit d_m increase from 1 to 5. Fig. 4.7 shows that as the deferment limit increases, the average cost will decrease. The deferment limit is the maximum number of time slots for which the operation of the load is allowed to be postponed in each stage. As the deferment limit increases, the scheduler has more flexibility to instruct the operation of the load. As a result, the scheduler can avoid running the load when the power price is high, and wait for the lower power price in the future time slots. It is also observed from Fig. 4.7 that if the scheduler can select the standby channel to access, for each deferment limit setting, the costs in Cases 2 and 3 will be lower than those of their counterparts without the standby channel. The average cost of the “always defer” policy also decreases as the deferment limit increases. When the deferment limit is 1, the average cost in Case 2 without the standby channel is little higher than that of the “always defer” policy. The reason is that when the deferment limit is 1, the scheduler has small flexibility. As a result, the load has to run even though the power price is high. Besides, the average cost obtained in Case 2 is further deteriorated by the incomplete power price information. Again, the average cost of the

Figure 4.8: Impact of the number of stages on the average cost in three cases without and with the standby channel.

“always run” policy is far higher than that of others, and hence is not shown.

Impact of Varied Numbers of Stages

Finally let the number of stages increase from 1 to 5. Fig. 4.8 shows that as the number of stages increases, the average cost will increase. In each time slot, only one stage of the load can be finished. As the number of stages increases, the number of time slots required to finish all the stages will also increase. As a result, the power consumption cost will be higher. Besides, since a job needs more time slots to be finished, the probability that the queue is full will increase. Consequently, the job dropping cost will also increase. Again in Fig. 4.8, the average costs from Cases 2 and 3 with the standby channel are better than those of their counterparts without the standby channel. The average costs of the “always run” and “always defer” policies also increase as the number of stages increases.

4.7 Conclusion

We have studied the deferrable load scheduling problem under perfect and imperfect data communication channels. Then, we have extended our consideration to the cases when the standby alternative channel can also be used to improve the reliability of power price information transfer. The MDP and POMDP models have been formulated to obtain the scheduling policies. As expected, with the perfect communication channel, the cost of operating the deferrable load is the lowest. Also, using POMDP based scheduling algorithm, the average cost can be reduced compared with that when only the coarse information (i.e., average power price) is used. We have also observed that the extra cost caused by the incomplete power price information can be reduced by about 34% if the POMDP based scheduling algorithm is applied. To this end, if the standby channel is used, the extra cost can be further reduced.

Chapter 5

An Adaptive Scheduling of PHEV Charging: Analysis under Imperfect Data Communication

5.1 Introduction

Transportation is as known [129] to contribute about 20% of world energy-related greenhouse gases (GHG) emissions by the year of 2006. About 95% of energy consumed by transportation means (i.e., cars, ships, trains, and airplanes) is from fossil fuels (i.e., diesel and gasoline). The ecosystem of the earth is endangered by the air pollution, and the global warming caused by burning the oil-based fuels. On the other hand, the depletion of oil resources is expected to happen in a few decades [130]. Hence, it is necessary to increase the speed of shifting from fossil fuel-based vehicles (FBVs) to EVs. Due to the limitation of current battery techniques, in a near-term, PHEV is an appropriate interim choice for the shifting from FBVs to EVs. Compared with the fossil fuel-based vehicles, PHEVs are more friendly to the environment and has lower transportation cost (e.g., money paid for energy consumption per kilometer) [131, 132].

However, relatively long battery charging time hinders the popularity of the PHEV. In level-1 charging mode and level-2 charging mode, the charging will take a few hours to be completed [133]. Even in a DC fast charging mode, it still takes about tens of minutes to finish the charging [133]. To save customers' time, a battery replacement strategy can be adopted to increase the charging efficiency

at a charging station. It is assumed that the batteries in the PHEVs, especially in public PHEVs (e.g., taxis or buses), are standardized and can be easily dismounted from and mounted into vehicles. When the PHEV arrives at the charging station, a staff of the charging station can replace the depleted battery in the PHEV with a fully charged battery. The driver only needs to wait a short period of time for the replacement to be finished and then drives away. The dismounted battery will be charged by a charger in the charging station. After the charging process is completed, it can be served as a fully charged battery when a new customer arrives. Compared with traditional “park and charge” style, by adopting the battery replacement strategy, the usage efficiency of chargers can be exploited to a much larger extent, since the chargers will probably work in an offline mode even when no PHEV arrives.

In smart grid, to control power consumption during peak hours and to attain a more stable consumption profile, the demand response program [47] is implemented through enabling RTP [134]. With RTP, power price is usually set to be high during peak hours to constrain unnecessary power consumption. While, power price is set to be cheap to attract more consumers during off-peak hours. To reduce the power consumption cost paid by charging station owners, the PHEV charging should be scheduled to be adaptive to RTP. As the battery replacement strategy is adopted, the PHEV charging scheduling problem is transformed into a battery charging scheduling problem. By solving the scheduling problem, an optimal battery charging policy is obtained for a charging station.

As the penetrating of PHEVs and charging stations, the power demand from PHEV charging may increase as fast as the popularity of PHEVs. If the power demand from charging stations cannot be satisfied, the quality of PHEV charging service will be deteriorated. On the other hand, if the power demand increases unexpectedly, to ensure the stability of the power system with respect to the metric such as power frequency [135], the public utility has to buy a lot of on-demand power from power plants to ensure the balance between power demand and power supply. As a result, the power supply cost paid by the public utility will increase dramatically. Hence, the issue of power supply optimization arises with the purpose to reduce the power supply cost and to ensure the stability of power system. In this chapter, the power supply optimization problem is formulated as a multi-stage stochastic programming model. The uncertainty of power demand is taken into account by considering the probability distribution over all possible power demand scenarios. Apart from using historical data to construct the probability distribution as other papers did in the literature, we propose an algorithm to obtain the power demand distribution based on the battery charging scheduling model and the optimal charging policy. The power supply is composed of the power reserved day-ahead and the on-demand power bought in real time when the real-time power demand

cannot be satisfied by the reserved power. As the price of reserved power is lower than the on-demand power, the power supply cost can be reduced through solving the stochastic programming model. To further save the power supply cost, renewable source as well as energy storage devices are also considered in the power supply model.

The rest of this chapter is organized as follows. Section 5.2 presents system model. In Section 5.3, queueing analysis methods are used to build the transition matrix for the system states. Section 5.4 solves the battery charging scheduling problem in three cases. Section 5.5 deals with the issue of power supply optimization. Section 5.6 gives numerical results and explanations. Section 5.7 draws conclusion of the chapter.

5.2 System Model and Assumptions

5.2.1 Charging Station

As shown in Fig. 5.1, the charging station does not charge PHEVs directly. Instead, chargers are connected with batteries dismantled from arriving PHEVs. This is different from a conventional charging station, in which a driver has to wait until the battery in his/her car is fully charged, taking long time to finish. Using the battery replacement strategy, the driver only spends a few minutes at the station. The charging station is assumed to maintain several batteries used for the replacement. These batteries are fully charged at the beginning of a day. As PHEVs arrive, the number of fully charged batteries will decrease because of replacements. However, as the dismantled batteries are charged by chargers, the number of fully charged batteries will increase later. The total number of batteries (i.e., fully charged and dismantled) maintained by the charging station is assumed to be fixed. The dismantled batteries are from PHEVs, may have some residual power but have not been fully charged yet. The change of the number of dismantled batteries depends on the rate of PHEV arrivals and the efficiency of chargers. If a PHEV arrives and there is no fully charged batteries available, the PHEV will be rejected from service and go to another charging station.

5.2.2 Smart Grid Data Communication Infrastructure

When RTP is adopted, we assume that the power price can be divided into several levels from low to high. A Markov chain is used to model the transition of power price from the current time slot to the

Figure 5.1: System model for PHEV charging scheduling in a charging station.

next time slot [123]. As shown in Fig. 5.1, the real-time price is decided by the MDMS according to power demand and power production. The real-time price information will be transmitted to an energy consumption scheduler [117]. The scheduler will make a decision for all active chargers, i.e., to charge or not to charge batteries.

To save the cost paid for data communication, we assume that a cognitive radio technique is used for transferring real-time price information. In particular, the real-time pricing transmission is considered as a secondary service, which accesses a licensed channel opportunistically when it is not occupied by a primary user. Therefore, the licensed channel may be unavailable occasionally. Moreover, the transmission may suffer from interference, hardware malfunction, software failure, or even cyber attacks. When the data connection is unavailable, lacking of price information, the scheduling performance will be negatively affected. The scheduling performance considered in this chapter includes the power consumption cost and the number of rejected PHEVs due to lack of fully charged batteries upon their arrivals.

To analyze the impact of imperfect data connection on the scheduling performance of PHEV charging, we consider the scheduling problem in three cases.

Case 1: Perfect Channel

The channel for price information transmission is assumed to be perfect. The scheduler can always receive the power price information. Then, an optimal charging scheduling policy can be obtained.

With complete information about real-time price, the scheduling performance will be the best, which leads to the lowest cost of the charging station.

Case 2: Single Cognitive Radio Channel

However, the assumption of a perfect channel is not practical. To study how the scheduling performance of a charging station is affected by the imperfect data connection, only one channel is considered in this case. The scheduler can only obtain the power price information if the channel is available. Otherwise, an average price will be used to make a decision for chargers. Based on the incomplete and inaccurate price information, the scheduler cannot obtain an optimal policy. As a result, the scheduling performance in this case will be worse than that in Case 1.

The state of the channel is modeled as a two-state “on-off” Markov chain. The channel state transition matrix is expressed as follows:

$$\mathbf{C} = \begin{bmatrix} C_{0,0} & 1 - C_{0,0} \\ 1 - C_{1,1} & C_{1,1} \end{bmatrix} \quad (5.1)$$

where $C_{0,0}$ is the transition probability from the “unavailable” (i.e., “off”) state in the current time slot to “unavailable” state in the next time slot and $C_{1,1}$ is the transition probability from the “available” (i.e., “on”) state to “available” state. The first and the second rows of $\mathbf{C}$ correspond to the states “unavailable”, and “available”, respectively.

Case 3: Multiple Cognitive Radio Channels

The idea of redundancy design is applied in this case by considering multiple channels. The scheduler can optimally sense, and then access one of the available channels. We assume that the channel sensing result is always correct and the technique in cognitive radio can be applied. The scheduler will not receive the price information only when all the channels are not available in the same time slot. The effect of multiple channels on alleviating the scheduling performance degradation caused by the imperfect connection is studied in this case. Here, it is expected that the scheduling performance will be worse than that in Case 1, but be better than that in Case 2.

5.2.3 Power Supply Optimization

Because charging stations will consume a lot of power, it is prudent for the public utility to make an optimization on the power supply. Otherwise, unexpected power demand increase in the real time will require the public utility to buy a lot of on-demand power to supplement the insufficient power supply. As a result, the operating cost of the public utility will increase, which actually can be avoided if the power supply is optimized. Here, we only consider the power demand from charging stations. Except buying power from power plant, the public utility can also use the power generated by the renewable sources that are owned by the public utility itself to supply the power demand.

However, as the power consumption behavior of each charging station is influenced by PHEV arrival process, power price charged by the public utility, the number of chargers and batteries in a charging station, and most importantly, the charging scheduling policy taken by the charging station, the power demand of a charging station is uncertain to the public utility. Uncertainty also exists in the renewable source generation, because the generation of mainstream renewable sources such as solar panels and wind turbines are to a large extent rely on the weather condition. Hence, the stochastic programming [136] is applied for the power supply optimization.

Based on the battery charging scheduling part of this chapter, we can derive the power demand distribution over possible power demand scenarios. In addition, the renewable source generation is taken into consideration. Because the power generation of renewable sources (i.e., solar panels or wind turbines) is affected by the weather condition, several scenarios can also be used to characterize the stochastic renewable source generation. The distribution over the renewable source generation scenarios can be obtained from historical data.

Due to the uncertainties in the power demand of charging stations and power generation of renewable sources, the power supply decisions of the public utility are made into two steps [137]. In the first step that is named as unit commitment, the public utility reserves power from power plants one day ahead at reservation price, also called as forward price. The second step is economic dispatch. In this step, if the sum of the reserved power and the power supplied by renewable sources is less than the actual power demand, the public utility will buy on-demand power from the power plants at on-demand price, also called as option price. Because the reserved power is bought by the public utility one day ahead before the actual power demand reveals, the forward price is cheaper than the option price of the on-demand power.

In addition, we assume that the public utility can utilize the energy storage devices such as batteries with large volume, flywheels [138], and supercapacitors [139, 140] to storage the power when the price is cheap and to release the power when the price is high or the power demand is large.

To take the uncertainty in the power demand of charging stations and power generation of renewable sources, a multi-stage stochastic programming model is proposed to solve the power supply optimization problem. Each stage in the stochastic programming model represents a time period (e.g., one hour).

5.2.4 Scheduling Time Horizon

In practice, the characteristics of PHEV arrival process may be time-varying during a day. For an example, the PHEV arrival rate λ in the midnight will be probably smaller than that in the afternoon. To take the variant characteristics of PHEV arrival process into account, a day can be divided into several time intervals and a closing block as shown in Fig. 5.2. In different time intervals, the sequence of substochastic matrices used to describe PHEV arrival process can be different. For the closing block, at the end of day, a charging station is assumed to be closed for 2 or 3 hours. During the closing time, the battery replacement service is suspended. Instead, the status of equipment such as chargers will be checked. Malfunctions of hardware and software will be solved, and all dismantled batteries will be fully charged. The battery charging scheduling in this chapter will be only studied for the rest time of a day, which is composed by U time intervals shown in Fig. 5.2. Each time interval consists of several time slots. The battery charging scheduling is operated in a time-slotted basis. The scheduler solves for the optimal action (e.g., to charge or not charge) to be taken in each time slot. The time slot structure is shown in Fig 5.3. The real-time power price is obtained at the beginning of each time slot. Based on the power price and other system parameters such as number of dismantled batteries, PHEV arrival rate, number of chargers and so on, the scheduler takes the optimal action accordingly. Then batteries will be charged or charging will be postponed. At the end of each time slot, there are new PHEVs arriving at the charging station to replace batteries.

As shown in Fig. 5.2, time periods have the same number of time slots. Besides, usually the length of a time period is shorter than the length of a time interval. The power supply optimization problem is solved for $|\mathcal{T}|$ periods, where $|\mathcal{T}| = \{1, \dots, \hat{t}, \dots, \hat{T}\}$. The time horizon for the power supply optimization is the same as that for the battery charging scheduling.

Figure 5.2: The time interval divisions of a day.

Figure 5.3: Time slot structure for PHEV charging scheduling.

5.3 Queueing Analysis

In this section, we present the derivation of the system state transition matrix of the queueing model. The transition matrix will be defined separately for different actions of the scheduler. Here, we consider two actions to be taken by the scheduler in a time slot, i.e., to charge and to defer charging of dismantled batteries. Therefore, the action space $\mathcal{A}$ is defined as follows:

$$\mathcal{A} = \{a_1, a_2\}. \quad (5.2)$$

a_1 is the action to let the active chargers charge batteries (i.e., “charge”). a_2 is the action to postpone the active chargers from charging (i.e., “defer”). The active chargers means the chargers connected with dismantled batteries.

5.3.1 Arrival Process and Queueing Model

The arrival process of PHEVs and the charging process of batteries are modeled in a time-slotted basis. To model the correlated and bursty PHEV arrivals, a discrete-time batch Markovian arrival process (DBMAP) [141] is applied. Because batteries may start their charging processes at different state of charge (SOC) levels, a discrete-time phase-type (PH) distribution [142] is used to model the charging time of each battery. Hence, the charging station in this chapter can be formulated as a $DBMAP/PH/N/R$ queueing model, where N is the number of chargers in the charging station

and R is the number of total batteries.

The DBMAP process can be defined by a sequence of $V \times V$ substochastic matrices, $\{H_0, H_1, \dots, H_b, \dots, H_B\}$, where B is the maximum arrival batch size. V denotes the number of states that belong to the underlying discrete-time Markov chain $\mathbf{H}$ of the DBMAP process, where $\mathbf{H} = \sum_{b=0}^B H_b$. An element $H_b(j, j')$ in H_b represents that if at the current time slot, the Markov chain is at state j , then with conditional probability $H_b(j, j')$ the transition to state j' will cause a batch of b arrivals. The average PHEV arrival rate can be calculated as follows:

$$\lambda = \rho_v \left(\sum_{b=1}^B b H_b \right) \vec{1}. \quad (5.3)$$

ρ_v is the stationary probability distribution of the phases that belong to the underlying Markov chain of the DBMAP process. ρ_v can be obtained by solving $\rho_v \mathbf{H} = \rho_v$ and $\rho_v \vec{1} = 1$.

For the PH distribution, it can be defined as $(\beta, \mathbf{S})$. The definition of β is given as follows:

$$\beta = \{\beta_1, \beta_2, \dots, \beta_m, \dots, \beta_M\}. \quad (5.4)$$

In the context of charging process, β represents the probability distribution of a dismantled battery over all M phases (i.e., SOC levels) at the beginning of the charging process. β_m is the probability that the SOC level of a dismantled battery is in phase m . For example, the SOC level of a battery can be divided into three phases: “almost empty”, “one third charged”, and “two third charged”. $\mathbf{S}$ is a substochastic $M \times M$ matrix containing the transition probability between any two service phases. In this model, the transition probability from an SOC level i to its adjacent higher level $i + 1$ is equal to 1, which means being charged for one time slot, a battery’s SOC can be increased by one level. A dismantled battery will be fully charged when it is charged for one time slot at the last phase.

5.3.2 Transition Matrix for Action “Charge”

For the PH distribution used to describe the charging time, by using traditional methods [141, 143], the phases of n active chargers are described by a set of n variables, i.e., $\{\xi_1, \dots, \xi_n\}$, where ξ_σ , $\sigma \in \{1, 2, \dots, n\}$, denotes the current SOC level of the battery connected with the σ th active charger. ξ_σ takes a value from the set of phases $\{1, 2, \dots, M\}$. $(\beta, \mathbf{S})$ is used to track the variance of ξ_σ . Therefore, to track the phase variances of n active charger, a matrix with dimension M^n

needs to be generated, where M is the total number of phases. As n increases, M^n will increase very fast. Instead, we can model the charging processes of active chargers by using a distribution vector $\boldsymbol{\eta} = \{\eta_1, \dots, \eta_M\}$ as that did in [144] with the assumption that all chargers have identical capability, where η_m , $m \in \{1, 2, \dots, M\}$, is the number of active chargers at m th phase in the same time slot. A charger at the m th phase means that the battery connected with the charger is at the SOC level m . The number of all distribution patterns for n active chargers over M phases is equal to $\binom{n+M-1}{M-1}$, which will be much smaller than M^n . For an example, if $n = 10$ and $M = 3$, $M^n = 3^{10}$, while $\binom{n+M-1}{M-1} = 66$. The total number of active chargers at all phases can be obtained by $n = \sum_{m=1}^M \eta_m$. Let r denote the number of dismounted batteries, where $r \in \{1, \dots, R\}$. Therefore, we have $n = \min(r, N)$. Let v denote the underlying Markov chain's phase of the DBMAP process used to describe the arrivals of PHEV, where $v \in \{1, \dots, V\}$. The system state space of the proposed *DBMAP/PH/N/R* queueing system can be expressed as follows:

$$\Psi = \{(0, v) \cup (r, v, \eta_1, \dots, \eta_M)\}, \quad (5.5)$$

where $(0, v)$ corresponds to the case of $r = 0$ and there is no need to use $\boldsymbol{\eta}$ to track the states of chargers.

Then the transition matrix of the *DBMAP/PH/N/R* queueing system under action “charge” is given as follows:

$$\mathbf{P} = \begin{bmatrix} P_{0,0} & P_{0,1} & \cdots & P_{0,R} \\ P_{1,0} & P_{1,1} & \cdots & P_{1,R} \\ \vdots & \vdots & \ddots & \vdots \\ P_{R,0} & P_{R,1} & \cdots & P_{R,R} \end{bmatrix}, \quad (5.6)$$

where a transition block $P_{r,r'}$ in matrix $\mathbf{P}$ corresponds to the transition when the number of dismounted batteries changes from r in the current time slot to r' in the next time slot. The derivation of $P_{r,r'}$ can be different when r takes different integer values from the range $\{0, \dots, R\}$ as shown in (5.7)-(5.17). Here, it is assumed that $B \leq N \leq R$, where B is the maximum batch size of the DBMAP process. Nevertheless, the derivation for the general case is also straightforward, which we omit for brevity.

If $r = r'$, $P_{r,r'}$ can be derived as follows:

$$P_{0,0} = H_0, \quad (5.7)$$

$$P_{r,r} = H_0 \otimes L_{r,r}^{0,0} + H_1 \otimes L_{r,r}^{1,1} + \cdots + H_r \otimes L_{r,r}^{r,r}, \text{ if } 1 \leq r \leq B, \quad (5.8)$$

$$P_{r,r} = \sum_{k=0}^B H_k \otimes L_{n,n}^{k,k}, \text{ if } B+1 \leq r < R, \quad (5.9)$$

where $n = \min(r, N)$,

$$P_{R,R} = (H_0 + H_1 + \cdots + H_B) \otimes L_{N,N}^{0,0} + (H_1 + H_2 + \cdots + H_B) \otimes L_{N,N}^{1,1} + \cdots + H_B \otimes L_{N,N}^{B,B}. \quad (5.10)$$

$\otimes$ is the Kronecker product. $L_{n,n'}^{f,u}$ is a matrix consisting of transition probabilities from row vector $\boldsymbol{\eta}$ in the current time slot to $\boldsymbol{\eta}'$ in the next time slot when f out of n chargers finish charging at the end of current time slot, while u chargers initiate their charging at the beginning of the next time slot resulting in n' active chargers in the next time slot. The derivation of $L_{n,n'}^{f,u}$ will be given later.

- (5.7) corresponds to the case when no PHEV arrives, and the number of dismantled batteries remains 0.
- (5.8) corresponds to the cases in which the number of chargers that finish charging is equal to the number of arriving PHEVs. In other words, in (5.8), the number of batteries being fully charged is equal to the number of batteries being dismantled from arriving PHEVs. As a result, r is the same from the current time slot to the next time slot.
- Similar to (5.8), (5.9) corresponds to the cases that r remains the same. However, for brevity, (5.9) is expressed in a compact form. In (5.8), as $r \leq B$, the maximum PHEV batch size is limited by r , while in (5.9), the maximum batch size is B . Besides, in (5.9), if $r > N$, in $L_{n,n}^{k,k}$, the number of active chargers n is limited by N .
- In (5.10), as the number of dismantled batteries is equal to R , there is no fully charged batteries ready for replacement at the beginning of the current time slot. If at the end of current time slot, the number of batteries being fully charged (i.e., f) is less than the number of arriving PHEVs, some incoming PHEVs will be rejected for replacing their batteries. The calculation for the number of rejected PHEVs will be discussed in Section 5.4.

If $r < r'$, $P_{r,r'}$ can be derived as follows:

$$P_{r,r'} = \sum_{k=r'-r}^b H_k \otimes L_{r,r'}^{k-(r'-r),k}, \quad b = \min(r', B), \quad (5.11)$$

if $0 \leq r \leq N, 1 \leq r' \leq N, r' - r \leq B$,

$$P_{r,r'} = \sum_{k=r'-r}^B H_k \otimes L_{n,N}^{k-(r'-r),k+(N+r-n)-r'}, \quad (5.12)$$

if $1 \leq r \leq R-1, N+1 \leq r' \leq R-1, r' - r \leq B$, where $n = \min(r, N)$,

$$P_{r,R} = \sum_{k=R-r}^B (H_k + H_{k+1} + \dots + H_B) \otimes L_{n,N}^{k-(R-r),k+(N+r-n)-R}, \quad (5.13)$$

if $1 \leq r \leq R-1, R-r \leq B$, where $n = \min(r, N)$,

$$P_{r,r'} = \mathbf{0}, \quad r' - r > B. \quad (5.14)$$

- In (5.11), each term in the summation corresponds to the case in which the number of dis-mounted batteries increases from r to r' under a combination of the number of batteries being fully charged and the batch size of arrived PHEVs. The first case in the summation is that there is no batteries being fully charged and the batch size is $r' - r$. As a result, r increases to r' . In (5.11), the maximum batch size is limited by B . When $r = 0$, (5.11) only has one term $H_r \otimes L_{0,r'}^{0,r'}$, where $L_{0,r'}^{0,r'}$ is a row vector consisting of probabilities that at the beginning of the next time slot r' chargers that just start their jobs formulate a certain η pattern. Each element of $L_{0,r'}^{0,r'}$ corresponds to a certain η . The $L_{0,r'}^{0,r'}$ will be derived later. The meaning of (5.12) is similar to (5.11). But r and r' take values different from that in (5.11).
- (5.13) also corresponds to the cases in which some PHEVs may be rejected. However, different from (5.10), it is expressed in a compact form. For each value taken by the variable k in the summation of (5.13), if the batch size is larger than k , some of arrived PHEVs will be rejected due to insufficient fully charged batteries. If the difference between r' and r is larger than the maximum batch size, then the transition from r to r' is impossible as indicated in (5.14). $\mathbf{0}$ is a zero matrix with appropriate size.

If $r > r'$, $P_{r,r'}$ is derived as follows:

$$P_{r,r'} = \sum_{k=0}^b H_k \otimes L_{r,r'}^{r-r'+k,k}, \quad b = \min(r', B), \quad \text{if } 1 \leq r \leq N, 0 \leq r' \leq N, \quad (5.15)$$

$$P_{r,r'} = \sum_{k=0}^b H_k \otimes L_{N,n}^{r-r'+k, r-(N+r'-n)+k}, \quad \text{if } N+1 \leq r \leq R, 1 \leq r' < R, \quad (5.16)$$

$$r - r' \leq N, \text{ where } b = \min(r' - r + N, B), \quad n = \min(r', N).$$

$$P_{r,r'} = \mathbf{0}, \quad r - r' > N, \quad (5.17)$$

- The first term in the summation of (5.15) corresponds to the case when $r - r'$ batteries are fully charged and no PHEV arrives. As a result, r decreases to r' . When $r' = 0$, (5.15) only has one term, i.e., $H_0 \otimes L_{r,0}^{r,0}$, where $L_{r,0}^{r,0}$ is a column vector consisting of probabilities that at the end of the current time slot, r active chargers in a certain η pattern all finish charging. Each element of $L_{r,0}^{r,0}$ corresponds to a certain η .
- For (5.16), when $r \geq N + 1$, the maximum number of batteries being fully charged in a time slot is limited by N . If there are N batteries being fully charged, the event that r decreases to r' only happens when the batch size of arriving PHEVs is equal to $r' - r + N$. However, the maximum batch size is limited by B . Hence, in (5.16), the maximum batch size b is equal to the minimum between $r' - r + N$ and B .
- If the difference between r' and r is larger than the total number of chargers, then the transition from r to r' is impossible as indicated in (5.17).

Given M (i.e., the number of battery's SOC levels) and n (i.e., the number of active chargers in the current time slot), we use a recursive algorithm to find all possible patterns of $\eta = \{\eta_1, \dots, \eta_{M-1}, \eta_M\}$ in the current time slot, where $\sum_{m=1}^M \eta_m = n$. As aforementioned, the number of all possible patterns is $\binom{n+M-1}{M-1}$. In the same way, given n' (i.e., the number of active chargers in the current time slot), all possible patterns of η' in the next time slot can be obtained. If $n = 0$, η has only one pattern (i.e., $\{0, 0, \dots, 0\}$). So does η' , if $n' = 0$. Because when action “charge” is taken, η_M active chargers will finish their charging at the end of the current time slot. As a result, the vector η becomes $\tilde{\eta} = \{0, \eta_1, \dots, \eta_{M-1}\}$. Then, PHEVs may arrive at the charging station to replace batteries. Alternatively, if all chargers are occupied previously, some dismantled batteries can get connected with chargers, because η_M chargers become idle now. As a result, $\tilde{\eta}$ will change to η' at

the beginning of the next time slot. The difference between $\tilde{\eta}$ and η' can be calculated as follows:

$$\delta = \{\delta_1, \delta_2, \dots, \delta_M\} = \{\eta'_1, \eta'_2 - \eta_1, \dots, \eta'_M - \eta_{M-1}\}, \quad (5.18)$$

where δ_m , for $1 \leq m \leq M$, represents the number of chargers that start charging batteries from the m th phase after new PHEVs arrive and dismount these batteries. Therefore, $\sum_{m=1}^M \delta_m = u$. In $L_{n,n'}^{f,u}$, each row represents a possible pattern of η , while each column represents a possible pattern of η' . Let $L(\eta, \eta')$ denote an element in $L_{n,n'}^{f,u}$ corresponding to the transition from η to η' . The calculation of $L(\eta, \eta')$ can be summarized as follows:

$$L(\eta, \eta') = \begin{cases} 0, & \text{if } \eta_M \neq f \\ 0, & \text{if } \exists \delta_m < 0 \\ \binom{u}{\delta_1} \beta_1^{\delta_1} \binom{u-\delta_1}{\delta_2} \beta_2^{\delta_2} \dots \binom{\delta_M}{\delta_M} \beta_M^{\delta_M}, & \text{otherwise.} \end{cases} \quad (5.19)$$

- The first condition in (5.19) corresponds to the case when for a certain η , it is impossible that f chargers finish charging at the end of current time slot.
- The second condition corresponds to the case when the vectors η and η' do not match with each other.
- The third condition corresponds to the feasible case in which the initial distribution vector β is used to calculate the probability.

(5.19) is applicable when $0 \leq n \leq N$, $0 < n' \leq N$, $0 \leq f \leq n$ and $0 < u \leq n'$. For the case when $u = 0$, if $\eta_M = f$ and all elements in δ are zero, $L(\eta, \eta') = 1$. Otherwise, $L(\eta, \eta') = 0$. The above procedures are also applicable for calculating $L_{0,r'}^{0,r'}$ and $L_{r,0}^{r,0}$.

Following all the above procedures, the system transition matrix $\mathbf{P}$ for the proposed *DBMAP* / *PH* / *N* / *R* queueing system under action “charge” can be established.

5.3.3 Transition Matrix for Action “Defer”

When action “defer” is taken, all active chargers will be stopped from charging batteries. The derivations of $P_{r,r'}$ is given in (5.20)-(5.25).

If $r = r'$, $P_{r,r'}$ can be derived as follows:

$$P_{0,0} = H_0, \quad (5.20)$$

$$P_{r,r} = H_0 \otimes L_{n,n}^0, \text{ if } 1 \leq r < R, \quad (5.21)$$

where $n = \min(r, N)$,

$$P_{R,R} = \left(\sum_{k=0}^B H_k \right) \otimes L_{N,N}^0. \quad (5.22)$$

$L_{n,n'}^u$ denotes the transition probability matrix for row vector η when action “defer” is taken. f is omitted, because no charger finishes its charging. (5.20) has the same meaning as (5.7). In (5.21), only when there is no arriving PHEV, r can remain the same. In (5.22), there are PHEVs being rejected, if the batch size is larger than 0.

If $r < r'$, $P_{r,r'}$ can be derived as follows:

$$P_{r,r'} = H_{r'-r} \otimes L_{n,n'}^{n'-n}, \text{ if } 0 \leq r < R, 1 \leq r' < R, r' - r \leq B, \quad (5.23)$$

where $n' = \min(r', N)$, $n = \min(r, N)$,

$$P_{r,R} = \left(\sum_{k=R-r}^B H_k \right) \otimes L_{n,N}^{N-n}, \text{ if } 1 \leq r < R, R - r \leq B, \quad (5.24)$$

where $n = \min(r, N)$,

$$P_{r,r'} = \mathbf{0}, \text{ if } r' - r > B. \quad (5.25)$$

In (5.23), when $r = 0$, $1 \leq r' \leq B$ and $L_{n,n'}^{n'-n}$ becomes $L_{0,r'}^{r'}$, is a row vector similar to $L_{0,r'}^{0,r'}$. In (5.24), if the batch size is larger than $R - r$, some arriving PHEVs will be rejected from service. (5.25) has the same meaning as (5.14).

If $r > r'$, $P_{r,r'} = \mathbf{0}$. Because when action “defer” is taken, r cannot decrease.

For the calculation of $L_{n,n'}^u$, because no batteries will be charged if action “defer” is taken, the vector η will be the same till the end of the current time slot. Then the vector δ that represents the distribution of starting chargers over battery's SOC levels can be calculated as follows:

$$\delta = \{\delta_1, \delta_2, \dots, \delta_M\} = \{\eta'_1 - \eta_1, \dots, \eta'_M - \eta_M\}. \quad (5.26)$$

Then the transition probability $L(\eta, \eta')$ in the matrix $L_{n,n'}^u$, where $0 \leq n \leq N$, $0 < n' \leq N$,

$0 < u \leq n'$, can be calculated as follows:

$$L(\boldsymbol{\eta}, \boldsymbol{\eta}') = \begin{cases} 0, & \text{if } \exists \delta_m < 0 \\ \binom{u}{\delta_1} \beta_1^{\delta_1} \binom{u-\delta_1}{\delta_2} \beta_2^{\delta_2} \cdots \binom{\delta_M}{\delta_M} \beta_M^{\delta_M}, & \text{otherwise.} \end{cases} \quad (5.27)$$

The meanings of the first and the second conditions in (5.27) are similar to those in (5.19). For the case when $u = 0$, if all elements in $\boldsymbol{\delta}$ are zero, $L(\boldsymbol{\eta}, \boldsymbol{\eta}') = 1$. Otherwise, $L(\boldsymbol{\eta}, \boldsymbol{\eta}') = 0$.

The other steps for deriving the transition matrix under action “defer” are the same as those in the previous subsection. Note that for different time intervals, the procedures for deriving the transition matrices under action “charge” and action “defer” are the same. However, for different time intervals, different sequences of substochastic matrices (i.e., $\{H_0, H_1, \dots, H_B\}$) are applied.

5.4 Battery Charging Scheduling Formulation in Three Cases

As the battery replacement strategy is adopted, the PHEV charging scheduling problem is transformed into a battery charging scheduling problem which can be formulated as a MDP model defined as $\langle \mathcal{S}, \mathcal{A}, Q, \mathcal{F} \rangle$, where $\mathcal{S}$ is the state space, $\mathcal{A}$ is the action space as defined in (5.2), Q represents the transition probability matrix for different actions, and $\mathcal{F}$ is the immediate cost function defined for each state when different actions are taken.

5.4.1 Case 1: Perfect Channel

Firstly, we will solve the scheduling problem for an interval. In the end of this subsection, we will explain how to solve the scheduling problem over the time horizon which consists of several time intervals. In this case, the power price transmission is assumed to be perfect. Hence, there is no need to track the channel state in this case. Then based on the system state space Ψ defined in (5.5) for the queueing model, the state space of the MDP model in this case is given as follows:

$$\mathcal{S} = \{(g, 0, v) \cup (g, r, v, \eta_1, \dots, \eta_M)\}, \quad g = \{g_1, \dots, g_h\} \quad (5.28)$$

where r , v , and η_m , for $1 \leq m \leq M$, have the same meaning as those defined in (5.5). g denotes the price level state. The lowest and highest price levels are denoted as g_1 and g_h , respectively.

The transition probability matrices of the MDP model under action “charge” and action “defer” can be calculated as follows:

$$\mathbf{Q}(\text{charge}) = \mathbf{G} \otimes \mathbf{P}(\text{charge}), \quad \mathbf{Q}(\text{defer}) = \mathbf{G} \otimes \mathbf{P}(\text{defer}), \quad (5.29)$$

where $\mathbf{P}(\text{charge})$ is the transition matrix for action “charge”, which can be obtained from Section 5.3.2, while $\mathbf{P}(\text{defer})$ can be obtained from Section 5.3.3. $\mathbf{G}$ is the price state transition matrix.

For the immediate cost, two performance metrics are considered, i.e., the number of rejected PHEVs due to lack of fully charged batteries and the power consumption cost. The customers are dissatisfied if they are rejected from service. To build a good reputation for the charging station, the number of rejected PHEVs should be also minimized in addition to the cost. To balance between the objective of saving the power consumption cost and the objective of reducing the number of rejected PHEVs, a factor f_d is used to weight the loss of rejecting a PHEV. The immediate cost function for each system state i is given as follows:

$$F_i^{a_1} = f_d \chi_{r,\mathbf{H}}^{a_1} + f_g n, \quad F_i^{a_2} = f_d \chi_{r,\mathbf{H}}^{a_2}, \quad i \in \mathcal{S} \quad (5.30)$$

where f_g is the power consumption cost incurred by each active charger when the price state at system state i is g . Because we assume that all chargers are identical and the same amount of power is consumed in all service phases (i.e., SOC levels), f_g is the same for the n active chargers, where $n = \min(r, N)$. $\chi_{r,\mathbf{H}}^{a_1}$ and $\chi_{r,\mathbf{H}}^{a_2}$ denote the average number of rejected PHEVs if the action “charge” and action “defer” are taken, respectively. The calculation of $\chi_{r,\mathbf{H}}^{a_1}$ and $\chi_{r,\mathbf{H}}^{a_2}$ are given as follows:

$$\chi_{r,\mathbf{H}}^{a_1} = \begin{cases} 0, & \text{if } (r - \eta_M) + B \leq R \\ \rho_v \left(\sum_{b=R-(r-\eta_M)+1}^B (b + (r - \eta_M) - R) H_b \right) \vec{\mathbf{1}}, & \text{otherwise,} \end{cases} \quad (5.31)$$

$$\chi_{r,\mathbf{H}}^{a_2} = \begin{cases} 0, & \text{if } r + B \leq R, \\ \rho_v \left(\sum_{b=R-r+1}^B (b + r - R) H_b \right) \vec{\mathbf{1}}, & \text{otherwise.} \end{cases} \quad (5.32)$$

ρ_v is the stationary probability distribution of the phases that belong to the underlying Markov chain of the DBMAP process as defined in Section 5.3.1. The first conditions in (5.31) and (5.32) indicate that if the number of fully charged batteries (i.e., $R - (r - \eta_M)$ for action “charge” and $R - r$ for action “defer”) is larger than the maximum batch size B , it is impossible that an incoming PHEV

will be rejected. Compared the second condition in (5.31) with the second one in (5.32), it can be observed that if action “charge” is taken, η_M active chargers will finish their jobs so that more fully charged batteries can be provide to the incoming PHEVs compared with that when action “defer” is taken. As a result, $\chi_{r,\mathbf{H}}^{a_1}$ is usually smaller than $\chi_{r,\mathbf{H}}^{a_2}$.

Based on (5.29), (5.30), (5.31) and (5.32), applying the value iteration algorithm [126], we can formulate the battery charging scheduling problem as follows:

$$\mathcal{V}_i^*(t) = \min_{a \in \mathcal{A}} \left(F_i^a + \sum_{i' \in \mathcal{S}} q_{i,i'}^a \mathcal{V}_{i'}^*(t+1) \right), \quad \forall i \in \mathcal{S}, \quad (5.33)$$

where $q_{i,i'}^a$ represents the transition probability in matrix $\mathbf{Q}(a)$, a can be either action “charge” or “defer”, i and i' are the state in the current and the next time slots, respectively. From (5.33), we can find the optimal action for each state i at decision epoch t as follows:

$$a_i^*(t) = \arg \min_{a \in \mathcal{A}} F_i^a + \sum_{i' \in \mathcal{S}} q_{i,i'}^a \mathcal{V}_{i'}^*(t+1), \quad \forall i \in \mathcal{S}. \quad (5.34)$$

Let T denote the length of the finite time horizon. T is equal to the number of all time slots that separately belong to U intervals in a day as shown in Fig. 5.2. Finally, we can find the optimal policy $\{a_i^*(1), a_i^*(2), \dots, a_i^*(T)\}$ and solve the battery charging scheduling problem in Case 1.

For different time intervals u and u' , $\mathbf{Q}_u(\text{charge})$ can be different from $\mathbf{Q}_{u'}(\text{charge})$. $\mathbf{Q}_u(\text{defer})$ can be different from $\mathbf{Q}_{u'}(\text{defer})$. Denote the last interval as U . The value iteration defined in (5.33) is applied first to the last time slot in interval U . For the iterations processed for interval U , the state transition matrices $\mathbf{Q}_U(\text{charge})$ and $\mathbf{Q}_U(\text{defer})$ are applied in (5.33). Then, the iteration is repeated one time slot by one time slot, and backwards until reaching the first time slot of the first time interval of the scheduling horizon. In each time interval u , its corresponding transition matrices $\mathbf{Q}_u(\text{charge})$ and $\mathbf{Q}_u(\text{defer})$ are applied.

5.4.2 Case 2: Single Cognitive Radio Channel

In this case, only one licensed channel is available and can be used to transfer price information. The scheduler cannot receive the price information if the channel is occupied by a primary user.

The system state space in this case can be expressed as follows:

$$\begin{aligned} \mathcal{S} &= \{(w, g, 0, v) \cup (w, g, r, v, \eta_1, \dots, \eta_M)\}, \\ g &= \{g_1, \dots, g_h\}, w = \{0, 1\}, \end{aligned} \quad (5.35)$$

where w represents the state of the licensed channel that can be “unavailable” or “available”, denoted by “0” and “1”, respectively.

Based on the channel state transition probabilities given in (5.1) and the price state transition matrix $\mathbf{G}$, we can obtain transition matrix $\mathbf{J}$ for the combination of the channel state w and the price state g . The matrix $\mathbf{J}$ can be obtained as follows:

$$\mathbf{J} = \begin{bmatrix} C_{0,0}\mathbf{I} & (1 - C_{0,0})\mathbf{I} \\ (1 - C_{1,1})\mathbf{G} & C_{1,1}\mathbf{G} \end{bmatrix}. \quad (5.36)$$

In the first row of matrix $\mathbf{J}$, the channel state in the current time slot is “unavailable”. As a result, the scheduler cannot observe the price level, and the identity matrix $\mathbf{I}$ with an appropriate size is applied (i.e., there is no change of price level from the scheduler’s perspective). In the second row of matrix $\mathbf{J}$, the channel state in the current time slot is “available”, which makes the price level be observable to the scheduler. Therefore, the matrix $\mathbf{G}$ is applied. Then, with matrix $\mathbf{G}$ in (5.29) being replaced by matrix $\mathbf{J}$, the transition probability matrices of the MDP model in Case 2 can be obtained.

For the immediate cost, $F_i^{a_1}$ in this case is different from its counterpart in Case 1, because if the channel is not available, the average price will be used as an estimate of the actual price. Let f_{ave} denote the power consumption cost per charger per time slot corresponding to the average price. The definition of f_{ave} is given as follows:

$$f_{ave} = \boldsymbol{\rho}_g [f_{g_1}, \dots, f_{g_h}]^T, \quad (5.37)$$

where f_{g_1} and f_{g_h} are the power consumption costs corresponding to the lowest and highest prices, respectively. $\boldsymbol{\rho}_g$ is the stationary probability row vector of price state g . $\boldsymbol{\rho}_g$ can be obtained by solving $\boldsymbol{\rho}_g \mathbf{G} = \boldsymbol{\rho}_g$ and $\boldsymbol{\rho}_g \vec{\mathbf{1}} = 1$. Then $F_i^{a_1}$ is redefined as follows:

$$F_i^{a_1} = \begin{cases} f_d \chi_{r,\mathbf{H}}^{a_1} + f_{ave} n, & \text{if } w = 0 \\ f_d \chi_{r,\mathbf{H}}^{a_1} + f_g n, & \text{otherwise.} \end{cases} \quad (5.38)$$

When action “defer” is taken, the definition of $F_i^{a_2}$ in this case is the same as its counterpart in Case 1.

The battery charging scheduling problem in Case 2 can be similarly formulated as in (5.33). The same as Case 1, the iteration in Case 2 is also applied first to the last time slot of the last time interval and backwards till the first time slot of the first time interval. However, the policy $\{a_i^*(1), a_i^*(2), \dots, a_i^*(T)\}$ obtained in Case 2 is called pseudo-optimal, because the price information used in the scheduling process is incomplete and the average price is inaccurate. Though the pseudo-optimal policy is applied by the scheduler, we should use the actual immediate cost function $\tilde{F}_i^a$ in which the average cost f_{ave} is substituted by the actual power price f_g and the actual transition matrix $\tilde{\mathbf{Q}}$ in which the matrix $\mathbf{G}$ is always applied to calculate the actual cost. The actual total cost can be calculated as follows:

$$\mathcal{V}_i^*(t) = \tilde{F}_i^{a^*} + \sum_{i' \in \mathcal{S}} \tilde{q}_{i,i'}^{a^*} \mathcal{V}_{i'}^*(t+1), \quad \forall i \in \mathcal{S}, \quad (5.39)$$

where $\mathcal{V}_i^*(t)$ represents the actual total cost at state i in the t th time slot when the pseudo-optimal action a^* is taken and actual immediate cost function $\tilde{F}_i^a$ is applied. $\tilde{q}_{i,i'}^{a^*}$ is the transition probability in the modified matrix $\tilde{\mathbf{Q}}$ when action a^* is taken.

5.4.3 Case 3: Multiple Cognitive Radio Channels

In this case, there can be multiple licensed channels. At the beginning of a time slot, the scheduler will sense and choose one of the available channels to access. Compared with Case 2, the probability that the scheduler cannot receive the price information will be smaller. In this case, the states of multiple channels are tracked. As a result, the system state space becomes

$$\begin{aligned} \mathcal{S} = & \left\{ (w_1, \dots, w_E, g, 0, v) \right. \\ & \left. \cup (w_1, \dots, w_E, g, r, v, \eta_1, \dots, \eta_M) \right\}, \\ & g = \{g_1, \dots, g_h\}, w_e = \{0, 1\}, \text{ for } e = 1, \dots, E, \end{aligned} \quad (5.40)$$

where w_e represents the state of licensed channel e .

Based on the transition probability matrix of each licensed channel similarly as defined in (5.1), the composite state transition probability matrix $\mathbf{W}$ for all E licensed channels can be obtained as

follows:

$$\mathbf{W} = \mathbf{C}_1 \otimes \cdots \otimes \mathbf{C}_e \otimes \cdots \otimes \mathbf{C}_E, \quad (5.41)$$

where $\mathbf{C}_e$, $1 \leq e \leq E$, represents the transition probability matrix of the e th channel.

Then the matrix $\mathbf{J}$ in Case 3 can be calculated as follows:

$$\mathbf{J} = \begin{bmatrix} \cdots & [\mathbf{W}]_{\text{disconnected}} \mathbf{I} & \cdots \\ \cdots & [\mathbf{W}]_{\text{connected}} \mathbf{G} & \cdots \\ \vdots & \vdots & \vdots \\ \cdots & [\mathbf{W}]_{\text{connected}} \mathbf{G} & \cdots \end{bmatrix}, \quad (5.42)$$

where $[\mathbf{W}]_{\text{disconnected}}$ and $[\mathbf{W}]_{\text{connected}}$ are the elements corresponding to the states that all channels are not available and the states that at least one channel is available, respectively. In the first row of $\mathbf{W}$, the states of all channels in the current time slot are not available. As a result, the scheduler is disconnected and the price information cannot be received. Hence, the identity matrix $\mathbf{I}$ with an appropriate size is applied. For the other rows of $\mathbf{W}$, at least one channel is available in the current time slot. As a result, the scheduler can access the available channel and receive the price information. Hence, the price state transition matrix $\mathbf{G}$ is applied. With matrix $\mathbf{G}$ in (5.29) being replaced by matrix $\mathbf{J}$ defined in (5.42), the transition probability matrices of the MDP model in Case 3 can be obtained.

For the immediate cost in Case 3, the prerequisite in the first condition of (5.38) should be revised as: if all channels are not available, the average power price is used.

The other steps of the battery charging scheduling problem formulation are similar to those in Case 2.

5.5 Power Supply Optimization

In this section, firstly we will show an algorithm used to theoretically derive the probability distribution over a set of possible power demand scenarios. Then, a multi-stage stochastic programming model for solving the power supply optimization problem is formulated. In the end, we transform it into an equivalent deterministic model which can be solved by standard linear programming solvers.

5.5.1 Power Demand Distribution

Even though the power demand of charging stations is uncertain, we can still predict it through the probability distribution. In this subsection, an algorithm used for deriving the power demand distribution of multiple charging stations will be shown. The power demand can be considered as the expected power consumption if the optimal charging policy obtained in Section 5.4 is adopted by the scheduler of the charging station. Hence, the algorithm is developed based on the formulation of battery charging scheduling problem given the optimal policy. We will only discuss the derivation of power demand distribution for Case 1. Nevertheless, for other cases, the derivation steps are similar.

In the next subsection, we will use a stochastic programming model to solve for the optimal reserved power and on-demand power for each time period. The definition of time period is given in Section 5.2.4. The uncertainty of power demand is taken into account by the stochastic programming model and described as the probability distribution over all possible cumulative power consumption scenarios that may appear in each time period of the scheduling horizon. The power consumption of charging stations is the power demand from the perspective of public utility. In the following, these two terms are used interchangeably.

We start with a single charging station. It is assumed that a charger will consume ΓkWh for one time slot. If a charging station has N chargers, then in each time slot, the maximum power consumption is $N\Gamma kWh$. Let a time period consist of $\hat{k}$ time slots. The cumulative power consumption scenarios of a charging station over a time period can be represented by the set $\mathcal{D} = \{0 kWh, \Gamma kWh, 2\Gamma kWh, \dots, N\hat{k}\Gamma kWh\}$, where the size of the set $\mathcal{D}$ is $N\hat{k} + 1$. The algorithm used for obtaining the probability distribution over all possible cumulative power consumption scenarios of each time period is shown in Algorithm 2.

The algorithm starts from the first time slot in the first period. As shown in the step 2 of Algorithm 2, in the first time slot, the cumulative power demand distribution of each state over the power demand set $\mathcal{D}$ is initialized. Each element of $\mathbf{d}_i^t$ represents a probability that the charging station cumulatively has consumed d units of power and is at state i when the current time slot is t , where $d \in \mathcal{D}$. In the column vector $\mathbf{d}_i^t$, the top element corresponds to the smallest power demand (i.e., $0 kWh$) in set $\mathcal{D}$, while the bottom element corresponds to the highest power demand (i.e., $N\hat{k}\Gamma kWh$) in set $\mathcal{D}$. In steps 3-7, because t currently represents the first time slot of a period, if the optimal action in state i is to charge batteries, the probability of consuming $n\Gamma kWh$ of power is equal to the probability

Algorithm 2 Algorithm for calculating the cumulative power demand distribution

```

1: for all state  $i \in \mathcal{S}$  do
2:   Initialize a column vector  $\mathbf{d}_i^t$ . All elements in  $\mathbf{d}_i^t$  are set to 0.  $\{\mathbf{d}_i^t$  is the cumulative power distribution
   for state  $i$ .  $|\mathbf{d}_i^t| = N\hat{k} + 1\}$ 
3:   if  $a_i^*(t) = a_1$  then
4:      $\mathbf{d}_i^t(n+1) = \tau_t(i)$ , where  $n = \min(r_i, N)$ .
5:   else
6:      $\mathbf{d}_i^t(1) = \tau_t(i)$ .
7:   end if
8: end for
9:  $t' = t + 1$  {Move to the next time slot}
10:  $t_s = t$  {Use  $t_s$  to denote the first time slot in this period}
11:  $\tau_{t'} = \tau_t^T \mathbf{Q}(\mu_t^*)$   $\{\mu_t^*$  is the optimal policy in time slot  $t$  (i.e.,  $\mu_t^* = \{a_1^*(t), \dots, a_{|S|}^*(t)\}\}$ 
12: repeat
13:   for all state  $i \in \mathcal{S}$  do
14:     for all state  $j \in \mathcal{S}$  do
15:       if  $a_i^*(t') = a_1$  then
16:          $\tilde{\mathbf{d}}_{j,i}^t = \text{shift}(\mathbf{d}_j^t, n) \cdot q_{j,i}^{a_j^*(t)}$ , where  $n = \min(r_i, N)$  {Shift all non-zeros elements in  $\mathbf{d}_j^t$  by
           $n$  positions downwards and time all elements by the transition probability  $q_{j,i}^{a_j^*(t)}$ }
17:       else
18:          $\tilde{\mathbf{d}}_{j,i}^t = \mathbf{d}_j^t \cdot q_{j,i}^{a_j^*(t)}$  {The cumulative power consumption will not increase}
19:       end if
20:     end for
21:      $\mathbf{d}_i^{t'} = [\tilde{\mathbf{d}}_{1,i}^t, \tilde{\mathbf{d}}_{2,i}^t, \dots, \tilde{\mathbf{d}}_{|S|,i}^t]$  {Construct a matrix in which each element is a column vector  $\tilde{\mathbf{d}}_{j,i}^t$ ,  $j \in \mathcal{S}$ }
22:      $\mathbf{d}_i^{t'} = \text{sum}(\mathbf{d}_i^{t'}, \text{row})$  {Sum each row of matrix  $\mathbf{d}_i^{t'}$  to change  $\mathbf{d}_i^{t'}$  into a column vector}
23:   end for
24:    $t' = t' + 1$  {Move to the next time slot and use  $t'$  to denote the new time slot}
25:    $t = t'$  {Use  $t$  to denote the previous time slot}
26:    $\tau_{t'} = \tau_t^T \mathbf{Q}(\mu_t^*)$ 
27: until  $t' = t_s + \hat{k}$ 
28:  $\mathbf{d}^{t_s, t_s + \hat{k} - 1} = [\mathbf{d}_1^{t_s + \hat{k} - 1}, \mathbf{d}_2^{t_s + \hat{k} - 1}, \dots, \mathbf{d}_{|S|}^{t_s + \hat{k} - 1}]$ 
29:  $\mathbf{d}^{t_s, t_s + \hat{k} - 1} = \text{sum}(\mathbf{d}^{t_s, t_s + \hat{k} - 1}, \text{row})$   $\{\mathbf{d}^{t_s, t_s + \hat{k} - 1}$  is transformed into a column vector that represents the
   cumulative power demand distribution for the time period starting from time slot  $t_s$  and ending in time
   slot  $t_s + \hat{k} - 1\}$ 
30:  $t = t_s + \hat{k}$ 
31: Go to step 1 {Calculate the power demand distribution for the next time period}

```

that the system is at state i in time slot t (i.e., $\tau_t(i)$). n represents the number of active chargers in state i and r_i is the number of dismantled batteries in state i . τ_t represents the probability distribution over all states in time slot t . If the optimal action is to defer charging, the charging station will consume no power with probability $\tau_t(i)$ as shown in step 6. In steps 9-11, we update the indices of time slot and the probability distribution over all states. $\mathbf{Q}(\mu_t^*)$ is the system transition matrix under the optimal policy μ_t^* . From steps 13 to 26, in the new time slot t' , for each state i , we calculate the probability that the charging station cumulatively has consumed certain amount of power from the first time slot t_s in this period till the current time slot t' , while the system transits to state i . The method is to add the power consumption in state i to the respective cumulative power consumption of each state j in the previous time slot t . To add the power consumption is done by shifting the non-zeros elements of $\mathbf{d}_j^t$ by n positions downwards (i.e., $\text{shift}(\mathbf{d}_j^t, n)$). All elements in the shifted vector should be multiplied by the transition probability from state j to state i as shown in step 16. For each (j, i) pair, the cumulative power consumption distribution is denoted as $\tilde{\mathbf{d}}_{j,i}^t$. If there is no power consumption in state i , $\mathbf{d}_j^t$ does not need to be shifted. $\tilde{\mathbf{d}}_{j,i}^t$ is obtained as shown in step 18. In step 22, by summing the probabilities that belong to different (j, i) pairs, but correspond to the same power consumption scenario, the probability distribution of cumulative power consumed by the charging station till time slot t' in this period is calculated given that the system is currently in state i . Repeat these steps for all states that the system may transit to in time slot t' . And then repeat the steps 13 to 26 for $\hat{k} - 2$ more time slots. After the demand distribution is calculated for each state in the last time slot of a period, by summing the distribution probabilities that belong to different states, but correspond to the same demand scenario as shown in step 28, we can eliminate the state condition and obtain the average power demand distribution of a charging station over this period. In the same way, we can calculate the cumulative power consumption distribution for the next time period. The algorithm stops when calculations for all time periods are finished.

To avoid confliction of notations, instead of $\mathbf{d}^{t_s, t_s + \hat{k} - 1}$ in step 29, let π_i^u denote the power demand distribution of the charging station i in the time period u , where $\pi_i^u = [\pi_{i,0}^u \cdots \pi_{i,\gamma}^u \cdots \pi_{i,N\hat{k}\Gamma}^u]$. $\pi_{i,\gamma}^u$ represents the probability that the charging station will consume γ kWh of power in the time period u . Then the power demand distribution of several charging stations in period u can be calculated as follows:

$$\pi^u = \bigodot_{i \in J^u} \pi_i^u, \quad (5.43)$$

where J^u represents the set of active charging stations in the time period u . $\odot$ is the convolution operator. The convolution of power demand distributions of two charging stations i and i' is defined

as follows:

$$\pi_d = \sum_{\{\gamma \in \mathcal{D}, \gamma' \in \mathcal{D}' | d = \gamma + \gamma'\}} \pi_{i,\gamma} \pi_{i',\gamma'}, \quad (5.44)$$

where $\mathcal{D}$ and $\mathcal{D}'$ are the sets of power demand scenarios of the charging station i and i' , respectively.

5.5.2 Stochastic Programming Model

A multi-stage stochastic programming model is proposed to solve the power supply optimization problem. Each stage represents a time period (e.g., one hour). In total, the power supply optimization problem is solved for $|\mathcal{T}|$ periods, where $\mathcal{T} = \{1, \dots, \hat{t}, \dots, \hat{T}\}$. The stochastic programming model takes the uncertainties existing in the power demand and power generation of renewable source into account. In $\hat{t}$ th period, the uncertainties are characterized by two sets of scenarios, $\mathcal{D}(\hat{t})$ and $\mathcal{R}(\hat{t})$ containing all possible scenarios that the power demand and the power generation of renewable source may reveal in the real time, respectively. The definitions of $\mathcal{D}(\hat{t})$ and $\mathcal{R}(\hat{t})$ are given as follows:

$$\mathcal{D}(\hat{t}) = \{d_1, \dots, d_\varphi\}, \mathcal{R}(\hat{t}) = \{r_1, \dots, r_\vartheta\} \quad (5.45)$$

where φ and ϑ are the last indexes of scenarios of the sets $\mathcal{D}(\hat{t})$ and $\mathcal{R}(\hat{t})$, respectively.

Let $\omega_{\hat{t}}$ denote a composite variable that represents a composite scenario of power demand and renewable source generation, defined as follows:

$$\omega_{\hat{t}} = \{d(\omega_{\hat{t}}), r(\omega_{\hat{t}}) | d(\omega_{\hat{t}}) \in \mathcal{D}(\hat{t}), r(\omega_{\hat{t}}) \in \mathcal{R}(\hat{t})\}. \quad (5.46)$$

The random variables, $d(\omega_{\hat{t}})$ and $r(\omega_{\hat{t}})$ represent the possible power demand scenario and renewable source generation scenario in stage t , respectively.

Let $\Omega_{\hat{t}}$ denote the composite scenario space at period $\hat{t}$, which is a Cartesian products of scenario spaces $\mathcal{D}(\hat{t})$ and $\mathcal{R}(\hat{t})$, as follows:

$$\Omega_{\hat{t}} = \mathcal{D}(\hat{t}) \times \mathcal{R}(\hat{t}). \quad (5.47)$$

The scenario space $\Omega_{\hat{t}}$ can be different from scenario space $\Omega_{\hat{t}'}$, where $\hat{t} \neq \hat{t}'$. Let Ω denote the composite scenario space over all $|\mathcal{T}|$ periods. The definition of Ω is given as follows:

$$\Omega = \prod_{\hat{t} \in \mathcal{T}} \Omega_{\hat{t}} = \Omega_1 \times \Omega_2 \times \dots \times \Omega_{\hat{T}} \quad (5.48)$$

which is a Cartesian product of all scenario spaces $\Omega_{\hat{t}}$, for $\hat{t} = \{1, \dots, \hat{T}\}$. Let ω denote a random variable that represents a overall composite scenario, where $\omega = (\omega_1, \omega_2, \dots, \omega_{\hat{t}}, \dots, \omega_{\hat{T}}) \in \Omega$.

To minimize the total cost spent by the public utility on buying reserved power and on-demand power from power plant, the stochastic programming model for the power supply optimization is formulated as follows:

$$z = \min \quad \mathbb{E}_{\Omega}[\Delta(\omega)], \quad (5.49)$$

$$\text{where} \quad \Delta(\omega) = \min_{x(\hat{t}), y_{\omega_{\hat{t}}}(\hat{t}), s(\hat{t})} \sum_{\hat{t} \in \mathcal{T}} x(\hat{t}) F_{re}(\hat{t}) + \sum_{\hat{t} \in \mathcal{T}} y_{\omega_{\hat{t}}}(\hat{t}) F_{on}(\hat{t}), \quad (5.50)$$

$$\text{subject to} \quad x(\hat{t}) + y_{\omega_{\hat{t}}}(\hat{t}) + (1 - \varepsilon)s(\hat{t}) \geq (1 - \varepsilon)s(\hat{t} + 1) + d(\omega_{\hat{t}}) - r(\omega_{\hat{t}}), \forall \hat{t} \in \mathcal{T}, \quad (5.51)$$

$$y_{\omega_{\hat{t}}}(\hat{t}) \leq G_{on}, \forall \hat{t} \in \mathcal{T}, \quad (5.52)$$

$$s(\hat{t}) - \varepsilon s(\hat{t}) \leq B^{bat}, s(1) - \varepsilon s(1) \leq B^{ini}, \forall \hat{t} \in \mathcal{T}, \quad (5.53)$$

$$x(\hat{t}) \geq 0, y_{\omega_{\hat{t}}}(\hat{t}) \geq 0, s(\hat{t}) \geq 0, \forall \hat{t} \in \mathcal{T}. \quad (5.54)$$

In (5.49), $\mathbb{E}[\cdot]$ represents the expectation over the random scenario variable $\omega_{\hat{t}}$, for all $t \in \mathcal{T}$. $x(\hat{t})$ denotes the amount of reserved power for period $\hat{t}$ in the unit commitment step. Because the reservation happens day-ahead, $x(\hat{t})$ is independent from the scenario variable $\omega_{\hat{t}}$. In contrast, because the on-demand power is bought according to the actual power demand and renewable source generation revealing at period $\hat{t}$, the amount of on-demand power $y_{\omega_{\hat{t}}}(\hat{t})$ depends on the scenario variable $\omega_{\hat{t}}$. $s(\hat{t})$ denotes the state of charge of the energy storage device at period $\hat{t}$ and ε is the power loss percentage due to self-discharge process. $F_{re}(\hat{t})$ and $F_{on}(\hat{t})$ are the forward price and option price for the reserved power and on-demand power at period $\hat{t}$, respectively.

In (5.50), the objective of function $\Delta(\omega)$ is to minimize the total cost given the overall composite scenario ω . The constraint in (5.51) is used to guarantee that the power demand can be satisfied by the power supply. If $s(\hat{t}) > s(\hat{t} + 1)$ which means that the energy storage device will discharge its power, then the power demand is from the charging stations alone. In this case, the power supply is composed of reserved power, on-demand power, power generated by renewable source and the power discharged from energy storage device. If $s(\hat{t}) < s(\hat{t} + 1)$ which means that the energy storage device will be charged by the grid, then the power demand is from the charging stations and the energy storage device. The constraint in (5.52) is used to limit the on-demand power within the maximum amount that can be provided by the power plants. In (5.53), the first term ensures that the power charged into the energy storage device will not exceed its capacity. The second term sets the initial power stored in the energy storage device. The last constraint in (5.54) ensures that all

variables are positive.

5.5.3 Deterministic Equivalent Formulation

To solve the stochastic programming model, the formulation in (5.49)-(5.54) can be transformed into the deterministic equivalent formulation (DEF) [136] given the probability distribution over scenario space $\Omega_{\hat{t}}$ is known for all $\hat{t} \in \mathcal{T}$. Let $p(\omega_{\hat{t}})$ denote the probability that the scenario $\omega_{\hat{t}}$ reveals at period $\hat{t}$. $p(\omega_{\hat{t}})$ can be obtained as follows:

$$p(\omega_{\hat{t}}) = p(d(\omega_{\hat{t}}))p(r(\omega_{\hat{t}})), \forall \omega_{\hat{t}} \in \Omega_{\hat{t}}, \forall \hat{t} \in \mathcal{T}. \quad (5.55)$$

$p(d(\omega_{\hat{t}}))$ is the probability that the power demand of charging stations at period $\hat{t}$ is $d(\omega_{\hat{t}})$ and $p(r(\omega_{\hat{t}}))$ is the probability that the power generation of renewable source at period $\hat{t}$ is $r(\omega_{\hat{t}})$. $p(d(\omega_{\hat{t}}))$ can be obtained from Section 5.5.1. $p(r(\omega_{\hat{t}}))$ is assumed to be obtained from historical data of renewable source generation. Then the deterministic equivalent formulation can be expressed as in (5.56)-(5.60). Compared with (5.49), in (5.56) the expectation $\mathbb{E}[\cdot]$ is realized by using the probability $p(\omega_{\hat{t}})$ as the weighting factor of the cost spent on buying the on-demand power in each scenario $\omega_{\hat{t}}$. Compared with constraints in (5.51)-(5.54), the constraints in (5.57)-(5.60) should be satisfied for all $\omega_{\hat{t}} \in \Omega_{\hat{t}}$.

$$z = \min_{x(\hat{t}), y_{\omega_{\hat{t}}}(\hat{t}), s(\hat{t})} \sum_{\hat{t} \in \mathcal{T}} x(\hat{t})F_{re}(\hat{t}) + \sum_{\hat{t} \in \mathcal{T}} \sum_{\omega_{\hat{t}} \in \Omega_{\hat{t}}} p(\omega_{\hat{t}})y_{\omega_{\hat{t}}}(\hat{t})F_{on}(\hat{t}), \quad (5.56)$$

$$\text{subject to} \quad x(\hat{t}) + y_{\omega_{\hat{t}}}(\hat{t}) + (1 - \varepsilon)s(\hat{t}) \geq (1 - \varepsilon)s(\hat{t} + 1) + d(\omega_{\hat{t}}) - r(\omega_{\hat{t}}), \quad (5.57)$$

$$\forall \hat{t} \in \mathcal{T}, \forall \omega_{\hat{t}} \in \Omega_{\hat{t}},$$

$$y_{\omega_{\hat{t}}}(\hat{t}) \leq G_{on}, \forall \hat{t} \in \mathcal{T}, \forall \omega_{\hat{t}} \in \Omega_{\hat{t}}, \quad (5.58)$$

$$s(\hat{t}) - \varepsilon s(\hat{t}) \leq B^{bat}, s(1) - \varepsilon s(1) \leq B^{ini}, \forall \hat{t} \in \mathcal{T}, \forall \omega_{\hat{t}} \in \Omega_{\hat{t}}, \quad (5.59)$$

$$x(\hat{t}) \geq 0, y_{\omega_{\hat{t}}}(\hat{t}) \geq 0, s(\hat{t}) \geq 0, \forall \hat{t} \in \mathcal{T}, \forall \omega_{\hat{t}} \in \Omega_{\hat{t}}. \quad (5.60)$$

The deterministic equivalent formulation in (5.56)-(5.60) shows a linear programming form. Hence, the standard linear programming solvers such as GAMS/CPLEX [145] can be adopted to solve for the optimal solutions, i.e., $x(\hat{t})$, $y_{\omega_{\hat{t}}}(\hat{t})$ and $s(\hat{t})$ for the amount of reserved power, the amount of on-demand power in each scenario, and the amount of power in the energy storage device, respectively. Some scenario reduction methods [146] can be applied to improve computational efficiency

of solving the power supply optimization problem.

5.6 Performance Evaluation

5.6.1 Parameter Setting

We assume that a charging station is closed from the hours from 02 : 00 to 04 : 00 for maintenance. The rest 22 hours in a day is divided into three intervals. Interval 1 is from 04 : 00 to 12 : 00. Interval 2 is from 12 : 00 to 20 : 00. Interval 3 is from 20 : 00 to 02 : 00. We consider a charging station with 6 chargers and 15 batteries. The 15 batteries are fully charged at the beginning of a scheduling horizon (i.e., 4AM). For the DBMAP process used to model the arrivals of PHEV, we consider a batch Bernoulli process in which each transition matrix H_b is a scalar value (i.e., the dimension of H_b is 1) indicating that a batch of b PHEVs arrives with probability H_b . The parameters of the Bernoulli process in three intervals are set so that the average PHEV arrival rate λ in Interval 3 is the lowest, while the average PHEV arrival rate in Interval 2 is the highest. The average PHEV arrival rate in Interval 1 is between those in Interval 2 and Interval 3. This is because the traffic in the street is heavier in Interval 2 than that in Interval 3. The length of a time slot is assumed to be 10 minutes. The maximum PHEV arrival batch size is set to 5 (i.e., the parameter B). For the PH distribution, we assume that the SOC of a battery carried by a PHEV that arrives at the charging station has three phases, i.e., almost empty, one third charged and two third charged. The distribution of all batteries carried by arriving PHEVs over the three phases is set to be $\{0.7, 0.2, 0.1\}$ (i.e., the vector β). The volume of each battery is assumed to be $30 kWh$ [133]. In each time slot, a charger can charge $10 kWh$ of power into a battery. We consider three power price levels: low, medium and high which have the prices of 10, 25 and 50 cents per kWh , respectively. The transition probabilities of the licensed channel in Case 2 are set to be $\{C_{0,0} = 0.4, C_{1,1} = 0.6\}$. The transition probabilities of the two licensed channels in Case 3 are set to be $\{C_{0,0}^1 = 0.4, C_{1,1}^1 = 0.6\}$ and $\{C_{0,0}^2 = 0.3, C_{1,1}^2 = 0.7\}$, respectively.

For the multi-stage stochastic programming model used for solving the power supply optimization problem, we assume that the length of each stage, or a time period, is one hour (i.e., 6 time slots). Based on the Algorithm 2 proposed in Section 5.5.1, we can obtain the power demand probability distribution in each hour over the composite power demand scenario space of 10 charging stations. For the renewable source generation, we consider both the power generated by the solar panels and

that generated by wind turbines. The scenario set of the renewable source generation is assumed to be $\{0 \text{ kWh}, 100 \text{ kWh}, 200 \text{ kWh}, \dots, 1000 \text{ kWh}\}$ [147]. The probability distribution over the power production scenario space is assumed to be random with an average of 800 kWh in the daytime (i.e., 07 : 00 to 18 : 00), and an average of 400 kWh in the nighttime (i.e., 18 : 00 to 07 : 00). The forward price and the option price are allowed to be period-varying. The lowest and the highest forward prices are set to 8.5, and 17.5 cents per kWh , respectively. The lowest and the highest option price are set to 12, and 21 cents per kWh , respectively. The volume of the energy storage device is 500 kWh [148]. Its self-discharge rate in each hour is 5%. The initial power in the energy storage device is 50 kWh .

5.6.2 Numerical Results

PHEV Charging Scheduling Performance in Three Cases

Figures 5.4(a), (b) and (c) show the average power consumption cost in different time slots of Intervals 1, 2 and 3, respectively. Figure 5.5 shows the probability of taking “charge” action in each time slot of the scheduling horizon. It is observed that the power consumption cost increases in Interval 1, and the first few slots of Interval 2. After it reaches the maximum point, the power cost decreases in the later few slots of Interval 2 and also in the Interval 3. This is due to the moderate PHEV arrival rate in Interval 1 and high PHEV arrival rate in Interval 2. To reduce the number of rejected PHEVs due to lack of fully charged batteries, the scheduler becomes more inclinable to allow the chargers to charge the batteries, even though sometimes the power price is at medium or high level. In the first few slots of Interval 1, as shown in Fig. 5.5, the probability of taking action “charge” increases rapidly. As a result, the power consumption cost increases very fast. After that, the probability of taking action “charge” saturates when it becomes high enough under the pressure of the PHEV arrival rate in Interval 1. As a result, the increasing rate of power consumption cost becomes slower. Because the PHEV arrival rate is larger in Interval 2 than that in Interval 1, to charge batteries faster so as to allow more PHEVs to replace their batteries, the probability of taking action “charge” increases to almost 100%. As a result, the power consumption cost increases in the first few slots of Interval 2. However, because the number of chargers in a charging station is limited, the power consumption cost reaches its maximum in about the middle of Interval 2. In the later slots of Interval 2, as the PHEV arrival rate is smaller in Interval 3, the scheduler becomes less inclinable to allow charging. Consequently, the probability of taking action “charge” as well as

the power consumption cost decreases. Although this will cause the number of rejected PHEVs to increase, the total cost (i.e., the sum of power consumption cost and the weighted cost of rejecting PHEVs) will not increase (for brevity, it is not shown here). In Interval 3, as the PHEV arrival rate is the lowest in the three intervals, the probability of taking action “charge” keeps decreasing and so does the power consumption cost.

In Case 2, because the licensed channel is not available occasionally, the scheduler cannot obtain the price information sometimes. Lack of complete information, misleading by the inaccurate average price, the scheduling policy obtained in Case 2 is not optimal. Compared with Case 1, it is more likely for the scheduler to allow chargers to work even when the power price is high. Hence, in Intervals 1 and 3, the power consumption cost in Case 2 is higher than that in Case 1. In Interval 2, because the probabilities of taking action “charge” in both Case 1 and Case 2 are very high (in some slots close to 100%), the difference of power consumption costs in Cases 1 and 2 due to optimality of policies is mitigated in this interval. The chargers are mostly allowed to charge batteries regardless of the current power price with the objective to provide more fully charged batteries to meet the more demand of arriving PHEVs. As a result, the power consumption costs in Case 1 and Case 2 are close to each other in most part of Interval 2. For Case 3, except the licensed channel in Case 2, there is one more channel that can be accessed. As a result, the probability of being disconnected in Case 3 will be much lower than that in Case 2. The scheduler in Case 3 will have more opportunities to receive the price information. Then, the scheduling policy obtained in Case 3 is better than that in Case 2, which leads to the lower power consumption cost in Case 3 than that in Case 2 and close to that in Case 1.

Figures 5.6(a), (b) and (c) show the average number of rejected PHEVs in time slots of Intervals 1, 2 and 3, respectively. At the beginning of Interval 1, even though the probability of taking action “charge” increases, the rate of batteries getting charged is still lagged behind the PHEV arrival rate. As a result, the number of dismantled batteries increases, which causes the number of rejected PHEVs increases in the first few slots of Interval 1. As the probability of taking action “charge” increases high enough, the number of dismantled and waiting batteries will decrease. Consequently, the number of rejected PHEVs decreases in later slots of Interval 1. In Interval 2, as the PHEV arrival rate is higher than that in Interval 1, the number of rejected PHEVs increases again. To save total cost, the probability of taking action “charge” decreases in later slots of Interval 2. As a result, the number of rejected PHEVs reaches its maximum in the end of Interval 2. At the beginning of Interval 3, the PHEV arrival rate is the lowest in the three intervals. Besides, even though in decreasing, the probability of taking action “charge” is still high enough. As a result, the

number of rejected PHEVs decreases. As the probability of taking action “charge” keeps decreasing for the remaining time slots of Interval 3, though the power consumption cost decreases, the number of rejected PHEVs increases slightly at the end of Interval 3.

As shown in Fig. 5.5, due to incomplete price information, the probability of taking action “charge” in Case 2 is slightly higher than that in Case 1. Consequently, in Intervals 1 and 3, the number of rejected PHEVs in Case 2 is usually slightly smaller than that in Case 1. Nevertheless, since higher power consumption cost is paid in Case 2, the total cost of Case 2 is still higher than that of Case 1. In Interval 2, as the probability of taking “charge” action is very high, the number of rejected PHEVs in Case 2 is almost the same as that in Case 1. For Case 3, similar to the power consumption cost, the number of rejected PHEVs in this case is more close to that in Case 1.

Results of Charging Scheduling Policies

Figure 5.7 shows the probabilities of taking action “charge” and at different price levels in Case 1 and Case 2, respectively. Following the definition of notations in Section 5.4, the probability can be expressed as $p(g, a^* = a_1)$. For Case 1, as the probability of taking action “charge” increases in Interval 1 as shown in Fig. 5.5, the probability $p(g = \text{low}, a^* = a_1)$, i.e., taking action “charge” while the price is at low level, increases to about 0.35 which is the stationary probability of power price being at the low level. It means that in Case 1, the chargers are always allowed by the scheduler to charge batteries when the power price is low, which is quite reasonable. However, for Case 2, when the actual price information cannot be obtained, the average price is used as an alternative. Even though the actual price may be at the low level, the average price used as an alternative is considered by the scheduler to be too high for chargers to charge dismantled batteries. As a results, in Intervals 1 and 3, the probability $p(g = \text{low}, a^* = a_1)$ in Case 2 is lower than that in Case 1, which causes the power consumption cost of Case 2 to be higher than that in Case 1 as shown in Figs. 5.4(a) and (c). In Interval 2, as the probability of taking action “charge” is close to 100%, the probability $p(g = \text{low}, a^* = a_1)$ in Case 2 also increases to about 0.35. The same reason causes the probability $p(g = \text{high}, a^* = a_1)$ increases to about 0.15 which is close to the stationary probability of the power price being at high level. Again, due to the incomplete price information, the probability $p(g = \text{high}, a^* = a_1)$ is higher in Case 2 than that in Case 1, which is another reason for the power consumption cost difference between Case 1 and Case 2.

Figures 5.8(a), (b) and (c) show the optimal battery charging scheduling policies in Case 1 taken by

the scheduler in the middle time slots of Intervals 1, 2 and 3, respectively. Following the notation defined in Section 5.4, the η factor in state $i \in \mathcal{S}$ is fixed. r (i.e., the number of dismounted batteries) changes from 6 to 15. The reason is that if r is less than 6 (i.e., the number of total chargers), the vector η cannot have the same pattern when r takes different values. The price state g varies from low to high. It is observed that in Interval 1, when the PHEV arrival rate is not very high, if the price is at medium level, the chargers are only allowed to work when r is larger than 7. However, if the price is at high level, to save power consumption cost, the chargers are only allowed to charge batteries when r is 16. The higher r is, the larger the number of rejected PHEVs will be. Therefore, the scheduler prefers to postpone charging when r is small, but turns to allow charging when r is high. In Interval 2, as aforementioned, the probability of taking action “charge” is very high. Hence, charging will be performed for all r states when price is low or medium. For the high price level, the scheduler allows charging as long as r is larger than 10. In Interval 3, as the PHEV arrival rate is the lowest in three intervals, compared with Interval 1, the “defer” action will be taken at more states.

Impact of Battery’s SOC Level Distribution on PHEV Charging Scheduling Performance

As mentioned in Section 5.3.1, the probability distribution of a battery over all SOC levels when it is dismounted from a PHEV is denoted as β . In different areas, the PHEV owners may have different battery replacement habits. For an example, in some areas where there are a lot of charging stations, batteries may usually be replaced when they are almost out of power. In the area with few charging stations (e.g., rural area), batteries may be replaced when they still have one third or two third of power. As a result, for charging stations located in different areas, the probability distribution β may be different. Figures 5.9(a) and (b) show the impact of β on the battery charging scheduling performance. β_1 is set to be $[0.7, 0.2, 0.1]$ for Area A in which most of PHEV owners prefer to replace their batteries when batteries are almost out of power. β_2 is set to be $[0.4, 0.3, 0.3]$ for Area B in which PHEV owners do not have very specific replacement preference. β_3 is set to be $[0.2, 0.3, 0.5]$ for Area C in which many PHEV owners prefer to replace their batteries when the batteries have two third of power or one third of power. From Fig. 5.9(a), it is observed that, as β changes from β_1 to β_3 , the power consumption costs in three cases decreases. Because compared with Area A , batteries replaced in the charging station located in Area C have more remaining power. Consequently, less power is consumed to fully charge the batteries, which leads to the reduction of power consumption cost. Moreover, the batteries replaced in Area C needs less time

to be fully charged. The replenishment rate of fully charged batteries in Area C is faster than that in Area A . Then more PHEVs can be served by the charging station in Area C . As a result, the number of rejected PHEVs decreases from Area A to Area C . However, for Areas A and C , the reduction of power consumption cost is not as significant as the number of rejected PHEV, because as the replenishment rate of fully charged batteries increases, additional admitted PHEVs will also contribute some part of power consumption cost.

Results of Power Demand Distribution and Power Supply Optimization

Figure 5.10 shows the composite power demand distribution of 10 charging stations. For simplicity, it is assumed that the power consumption behaviors of these charging stations are identical. The third hour in each interval (i.e., 07 : 00 to 08 : 00 for Interval 1, 15 : 00 to 16 : 00 for Interval 2 and 23 : 00 to 00 : 00 for Interval 3) is chosen for illustration. Compared with the hours in Intervals 1 and 2, in the hour of Interval 3, because the PHEV arrival rate is the lowest in three intervals and the probability of taking action “charge” is decreasing in Interval 3, for the hour 23 : 00 to 00 : 00, the probabilities are mainly distributed on the demand scenarios from $1.6 \times 10^3 kWh$ to $2.8 \times 10^3 kWh$. For the hour 07 : 00 to 08 : 00 in Interval 1, the probabilities are mainly distributed on the demand scenarios from $2.2 \times 10^3 kWh$ to $3.2 \times 10^3 kWh$. While for the hour 15 : 00 to 16 : 00 in Interval 2, as the PHEV arrival rate is the highest in three intervals and the probability of taking action “charge” is very high, the probabilities of power demand are mainly distributed on the demand scenarios above $3.2 \times 10^3 kWh$. From Fig. 5.10, it is observed that the average power demand in the hour 23 : 00 to 00 : 00 is the lowest in the three hours. The average power demand in the hour 15 : 00 to 16 : 00 is the highest. The average demand in the hour 07 : 00 to 08 : 00 is in the middle.

Figure 5.11 shows the average power demand of 10 charging stations, the average power generated by renewable sources, the power in energy storage device, the power reserved in the unit commitment step and the average on-demand power bought in the economic dispatch step of each hour over the time horizon considered for the power supply optimization problem. As expected, the peak power demand appears in the Interval 2. The reason can be easily learned from the results shown in Fig. 5.5 and Fig. 5.10. For the power generated by renewable sources, as the renewable sources under consideration includes solar panels as well as wind turbines, after the 15th hour (i.e., 18 : 00 o'clock), during the nighttime, the wind turbines can still generate power. Hence, the power generated by the renewable sources is nonzero during nighttime but still less than that generated in

daytime. As the forward price for reserving power supply in peak hours (i.e., when power demand is high) is higher than that in off-peak hours, the energy storage device starts being charged at the first hour, and decides to discharge when the power price starts to decrease. Therefore, less reserved power and on-demand power needs to be bought when price is high, which saves the power supply cost paid by the public utility. Because the forward price is always cheaper than the option price, the amount of reserved power in each hour is much larger than that of on-demand power.

In Fig. 5.12, the impact of renewable source capacity on the power supply cost is studied. As the average values of power generated in nighttime and daytime increase, the total power supply cost and the cost paid for reserved power decreases. The reason is that as the capacity of renewable source is expanded, more power can be supplied by the renewable source, which results in the decrease of reserved power. However, as the capacity of renewable source increases, the uncertainty of the renewable source generation will increase. As a result, the on-demand power will increase slightly as the capacity of renewable source increases. Even though, the increase of renewable source capacity can reduce power supply cost, the implementation cost of new renewable source facilities such as solar panels and wind turbines cannot be neglected. Hence the results shown in Fig. 5.12 can be used as reference when the public utility schedules the renewable source generation expansion.

5.7 Conclusion

We have considered the battery replacement strategy for a charging station of PHEVs. We have studied the batteries charging scheduling problem in three cases. In the first case, the real-time power price is always available (i.e., perfect channel). In the second and third cases, we have assumed that the power price may not be always available, where one or multiple communication channels could be available (i.e., one imperfect channel and multiple imperfect channels), respectively. In the problem formulation, a DBMAP process has been used to model correlated and batch arrivals of PHEVs. A phase-type distribution has been used to model the charging time. MDP models have been formulated and solved to obtain optimal charging policies for all cases. The numerical results show that the negative impact of imperfect price transmission on the scheduling performance measures.

Moreover, based on the battery charging scheduling model and the optimal charging policy, we have proposed an algorithm used for deriving the power demand distribution of several charging

stations in each period. The demand distribution derived from the algorithm and the renewable source generation distribution are used in the power supply optimization formulated as a multi-stage stochastic programming model. By solving the stochastic programming problem, the reserved power and on-demand power bought in each period are optimized for the public utility so as to achieve the lowest power supply cost.

(a)

(b)

(c)

Figure 5.4: Average power consumption cost in time slots of (a) Interval 1, (b) Interval 2, and (c) Interval 3.

Figure 5.5: The probability of taking action “charge” in each time slot.

(a)

(b)

(c)

Figure 5.6: Average number of rejected PHEVs in time slots of (a) Interval 1, (b) Interval 2, and (c) Interval 3.

Figure 5.7: The probabilities of taking action “charge” while price being high or low in Case 1 and Case 2.

(a)

(b)

(c)

Figure 5.8: Battery charging scheduling policy of Case 1 in (a) Interval 1, (b) Interval 2, and (c) Interval 3.

Figure 5.9: The impact of probability distribution over SOC levels on (a) average power consumption cost per slot, (b) average number of rejected PHEVs.

Figure 5.10: The power demand distribution of 10 charging stations.

Figure 5.11: Average power demand of 10 charging stations, power generated by renewable sources, power in energy storage device, reserved power and on-demand power of each hour.

Figure 5.12: Impact of renewable source capacity on power supply cost.

Chapter 6

Conclusions and Future Work

In this chapter, firstly the major contributions of our research are summarized. Then, possible future directions are discussed.

6.1 Major Research Contributions

For the medium access control for dynamic spectrum access discussed in Chapter 3, the contributions can be summarized as follows:

- The values of the channel state transition probabilities are permitted to be uncertain to some extent (i.e., interval uncertainty set), which leads to a robust optimization problem.
- We transform the robust optimization problem into a linear optimization problem by using methods that can solve Markov chain with uncertainty and obtain the lower bounds and upper bounds of the QoS measures.
- The analysis is useful for the design of a cognitive radio network when system parameters such as channel state transition probabilities cannot be assessed precisely.

For the deferrable load scheduling discussed in Chapter 4, the contributions can be summarized as follows:

- Based on the Markov decision process (MDP) and partially observable MDP (POMDP) mod-

els, the scheduling policy is obtained for the situations when the data connection for transferring the power price is always available and occasionally unavailable, respectively. The objective of the policy is to minimize the power consumption cost based on the deferrable load state and constraints.

- The impact of data communication unavailability on the power consumption cost is assessed through the scheduling policy obtained from MDP and POMDP models.
- The numerical results show that the proposed POMDP based deferrable load scheduling algorithm can effectively mitigate the impact of incomplete price information on the scheduling performance.
- We introduce the optimal channel selection scheme to provide an alternative of the power price information transfer. Besides the default channel between the scheduler and the network, the scheduler can also choose the standby channel to receive the power price information. The standby channel is assumed to be always available (e.g., 3G system), but accessing it incurs additional cost. An optimization problem is formulated and solved to obtain the optimal channel selection policy. The performance evaluation result shows that the power consumption cost can be reduced by using the standby channel.

For the PHEV charging scheduling discussed in Chapter 5, the contributions can be summarized as follows:

- A battery replacement strategy is applied instead of traditional “park and charge” style so as to save customers’ time and to improve the efficiency of chargers.
- The battery charging problem is formulated as a Markov decision process (MDP) problem from which an optimal charging policy for a charging station can be obtained with the objective to minimize the cost due to power consumption and customer’s dissatisfaction.
- The impact caused by data communication unavailability on the scheduling performance of a charging station is analyzed.
- Other than using historical data, an algorithm is proposed to theoretically derive the power demand distribution for one or several charging stations.
- The power supply cost of the public utility is saved by solving for the optimal reserved power and on-demand power from the stochastic programming model formulated for power supply optimization. The renewable source and energy storage device are taken in consideration.

6.2 Future Work

6.2.1 Future Work on Medium Access Control for Dynamic Spectrum Access

Through the performance analysis of a cognitive radio network, the feasibility and advantages of DSA strategy can be evaluated and verified. In the future, the performance analysis of cognitive radio networks can also evaluate the impact of wireless environmental characteristics (e.g., number of channels, primary users' behavior, secondary users' channel sensing, and accessing strategies) on the performances of system. The analytical model can be used for the selection of system parameters (e.g., buffer size and transmission rate) so that the system can operate reliably and optimally.

The implementation of cloud computing to facilitate the spectrum sensing and spectrum allocation [149, 150] in a cognitive radio network can also be a direction of my future research. With the aid of cloud computing, the storage of information pertaining to spectrum status and the work of running spectrum allocation algorithm can be offloaded from secondary users to a remote server with large storage volume and computational capability. In this way, the cost of a secondary device can be reduced, and the lifetime of a battery in a secondary device can be prolonged, which is beneficial to the popularity of cognitive radio networks. For my future research, the impact of uncertain parameters such as channel availability on the performance of dynamic spectrum access in a cloud computing based cognitive radio network can be studied.

6.2.2 Future Work on Deferrable Load Scheduling in Smart Grid

In the current work, the deferrable load is assumed to be interruptible at all stages when it is being processed. In the future, the load that cannot be interrupted once being started will be considered. The impact of incomplete price information on the scheduling performance of this kind of deferrable load will also be evaluated. Besides, the analysis can be applied to other subsystem in smart grid. For instance, there are smart meters or sensors on transmission lines, and in distribution systems. The impact of intermittent meter data on the performance of these subsystems can also be evaluated.

Another direction could be studying the impact of data communications' unavailability on the performance of direct load control [151]. Compared with the load scheduling studied in this thesis, which is performed by a scheduler at a consumer's premise, in direct load control program, the grid operator can directly turn off/on some networked appliances during peak hours (i.e., the hours when

the power supply could be insufficient) through remote utility-controlled switches [152], and shift the load of those appliances to off-peak hours. The control of participating appliances are transferred by consumers to the grid operator according to the contracts made between the two sides. The grid operator offers financial incentives to attract consumers to join this program. If the data communications are unavailable, the remote switches cannot receive the orders from the grid operator to turn off the appliances. As a result, the load curtailment objective cannot be achieved, which may endanger the stability of the grid system and incur penalty cost to the grid operator. In the off-peak hours, if the remote switches cannot receive the order to turn on the appliances, consumers will be dissatisfied with the service of this program. Therefore, an optimization problem can be formulated with consideration of both the load control benefit to the grid system and the satisfaction of consumers.

6.2.3 Future Work on PHEV Charging Scheduling in Smart Grid

In the current work, we only consider the impact of unavailability of price information on the scheduling performance. In the future, the effect of price falsification attack can be discussed. The communication system of smart grid may be intruded by attackers. The price information transmitted from operational center of grid could be falsified before it is received by the smart meter in consumers' residence. The price falsification attack can be used to disturb the stability of power grid or to increase the regulation cost of the grid.

For the battery charging, currently it is assumed that a charger can increase a battery's SOC by one level in a time slot. In the future, the performance of fast chargers with faster charging rate can be evaluated and compared with normal chargers. Besides, a charging station can also be assumed to have energy storage devices used to buffer power when price is cheap and to release power when power price is high so that the operating cost of a charging station can be reduced. On the other hand, the pressure caused by PHEV charging on the power grid can be analyzed. The PHEV charging can be scheduled to avoid power demand peak hours. If the PHEV charging can be scheduled to run in off-peak hours, the power demand can be more stable and the management cost of grid operator can be saved.

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Appendix A

List of Abbreviations

Abbreviation	Description
3G	Third Generation Mobile Telecommunication System
AC	Alternating Current
AMI	Advanced Metering Infrastructure
BMAP	Batch Markovian Arrival Process
BPSO	Binary Particle Swarm Optimization
BSS	Battery Switch Station
CD	Charge-Depleting
CS	Charge-Sustaining
CTMC	Continuous-Time Markov Chain
DAU	Data Aggregator Unit
DBMAP	Discrete-Time Batch Markovian Arrival Process
DC	Direct Current
DEF	Deterministic Equivalent Formulation
DoS	Denial-of-Service
DR	Demand Response

Abbreviation	Description
DSA	Dynamic Spectrum Access
DSM	Demand-Side Management
DTMC	Discrete-Time Markov Chain
ESD	Energy Storage Device
EV	Electric Vehicle
FBV	Fuel-Based Vehicle
GHG	Greenhouse Gas
HAN	Home Area Network
ICT	Information Communication Technologies
MAC	Medium Access Control
MDMS	Meter Data Management System
NAN	Neighborhood Area Network
PH	Phase-Type
PHEV	Plug-In Hybrid Electric Vehicle
QoS	Quality of Service
RTP	Real-Time Pricing
SNR	Signal to Noise Ratio
SOC	State of Charge
WAN	Wide Area Network
WiMAX	Worldwide Interoperability for Microwave Access
WRAN	Wireless Regional Area Network

Appendix B

Publication List

1. **Q. Dong**, D. Niyato, P. Wang, and Z. Han, “Deferrable load scheduling under imperfect data communication channel,” *Wireless Communications and Mobile Computing (WCMC)*, to appear.
2. **Q. Dong**, D. Niyato, P. Wang, and Z. Han, “An adaptive scheduling of PHEV charging: Analysis under imperfect data communication,” in *Proceedings of IEEE International Conference on Smart Grid Communications (SmartGridComm)*, Vancouver, Canada, 21-24 October 2013.
3. **Q. Dong**, D. Niyato, P. Wang, and Z. Han, “Deferrable load scheduling optimization under power price information attacks in smart grid,” in *Proceedings of IEEE Wireless Communications and Networking Conference (WCNC)*, Shanghai, China, 7-10 April 2013.
4. D. Niyato, **Q. Dong**, P. Wang, and E. Hossain, “Optimizations of power consumption and supply in the smart grid: Analysis of the impact of data communication reliability,” *IEEE Transactions on Smart Grid*, vol. 4, no. 1, pp. 21-35, March 2013.
5. **Q. Dong**, D. Niyato, P. Wang, and S. Gong, “Deferrable load scheduling of smart meter with intermittent communication connection,” in *Proceedings of IEEE International Conference on Smart Grid Communications (SmartGridComm)*, Tainan City, Taiwan, 5-8 November 2012.
6. **Q. Dong**, D. Niyato, and P. Wang, “Dynamic spectrum access for meter data transmission in smart grid: Analysis of packet loss,” in *Proceedings of IEEE Wireless Communications and Networking Conference (WCNC)*, Paris, France, 1-4 April 2012.

7. **Q. Dong**, D. Niyato, and P. Wang, “Medium access control for dynamic spectrum access in cognitive radio networks: Analysis under uncertainty,” *Wireless Communications and Mobile Computing (WCMC)*, published online in Wiley Online Library, January 2012.